EV uptake forecasting

2025-2030 Regulatory Proposal

Supporting document 5.7.11

20 December 2023 – Version 1

SA Power Networks

Empowering South Australia

GridFleet™

SAPN network-wide electric vehicle modelling

Methodology and assumptions report - 2022

[redacted]

Background

South Australian Power Networks (SAPN) is a large regulated utility delivering essential electricity distribution services to South Australians. To support this task, SAPN prepares detailed forecasts for demand and generation capacity as part of the network investment planning process.

SAPN has identified the potential need for significant investment requirements to support the uptake of electric vehicles and does not currently have a source for South Australian (SA) based Electric Vehicle (EV) demand forecasting, and requires this data to feed into network augmentation expenditure modelling.

As such, SAPN engaged Evenergi to provide postcode level forecasting for EV uptake and associated demand across SA over the 2025-2045 period, to assist in the development of regulatory submissions to the Australian Energy Regulator (AER) for the 2025-2030 regulatory control period.

Evenergi has developed a world-leading modelling platform called GridFleet™ which emulates the impacts of electric vehicles on the grid at a granular postcode level. This tool has been used to successfully model the impacts of EV charging on the network for DNSPs in New South Wales (NSW) and Western Australia (WA). This document describes the methodology, key assumptions and important insights from the modelling.

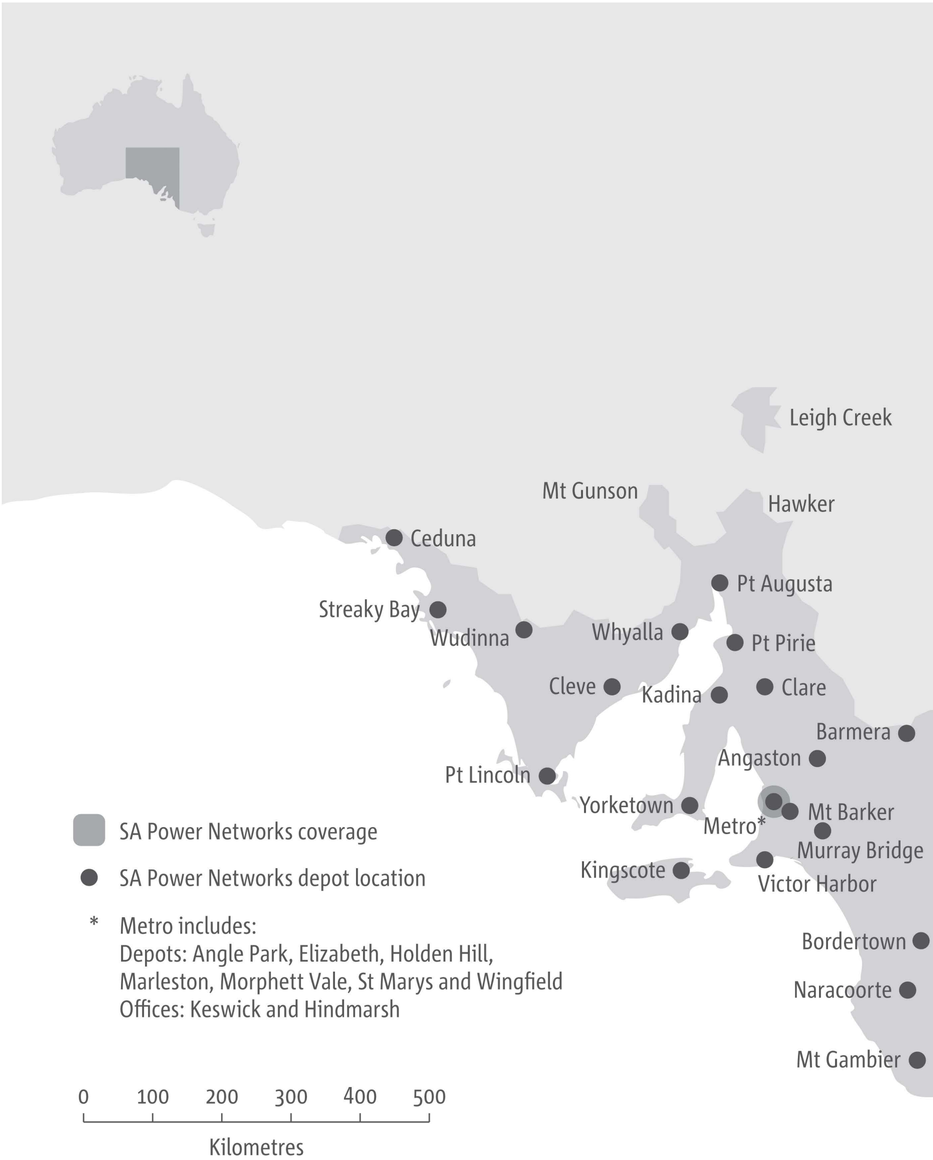


Figure 1: SAPN's network area

Key Objectives

The project aimed to achieve the following objectives:

1. EV uptake forecasts and tool: A postcode level forecast of EV uptake over a 20 year period from 2025 - 2045
    a. Forecasts must include at least high and low EV uptake scenarios in addition to a 'most likely' base case. Scenarios are to be developed collaboratively with SAPN to align with broader network planning and modelling. The impact of time of use tariffs and other network incentives should be considered.
    b. Each postcode musthave load profile types assigned to it, along with a number of chargers forecast to be installed in that area.
    c. Scaling factors to determine monthly demands from typical modelled days.
2. Load profiles: A set of 30-minute interval EV charging load profiles for a varied set of charging types
    a. Categories are subject to change depending on the capabilities of the consultant's model, but indicatively are:
        i. Residential charging
        ii. Commercial charging - Fleets, Bus depots
        iii. Public charging (including DC fast charging) - shopping centres, schools, community centres, hospitals, business districts, carparks
        iv. Logistics and freight
    b. At a minimum, operating scenarios shall include both weekend and weekday charging during periods of peak demand (summer months) and minimum demand (shoulder season spring/autumn months). Representative days are a suitable way to represent different periods throughout the year.
    c. Peak day impacts such as large increases in population at rural holiday towns such as Victor Harbor during the Christmas/New Year period must also be considered and included.
    d. Developed load profiles should account for customer behaviour in response to time of use tariffs.
3. Outputs of the model must be compatible with SAPN's network planning tools. Common data formats such as CSV or Excel.
4. All inputs, assumptions and methodologies used must be clearly outlined and explained.

GridFleet overview

GridFleet™ is a platform that enables DNSP forecasting teams to spatially allocate demand to specific geographical areas. It uses real, catalogued and emulated data to create load curves for summer, winter, weekday and weekend with a focus on annual peaks.

Most importantly, it includes all EV typologies that may impact a network - buses, car parks, DC fast charging, fleets and residential. By entering a specific area and some additional information, the tool can use its own data sources to produce load curves.

The model has been designed to be entirely configurable for forecasters who can manage and modify escalators for all assumptions. It also has a powerful scenario analysis tool that enables the user to modify high-impact assumptions across all typologies.

All the assumptions used in the tool are provided and many of them are user-configurable. In addition, the tool allows for new data sources such as locally completed surveys or locally connected vehicle data. For detailed overviews of the GridFleet™ model and its typologies, please refer to the respective documentation available from Evenergi.

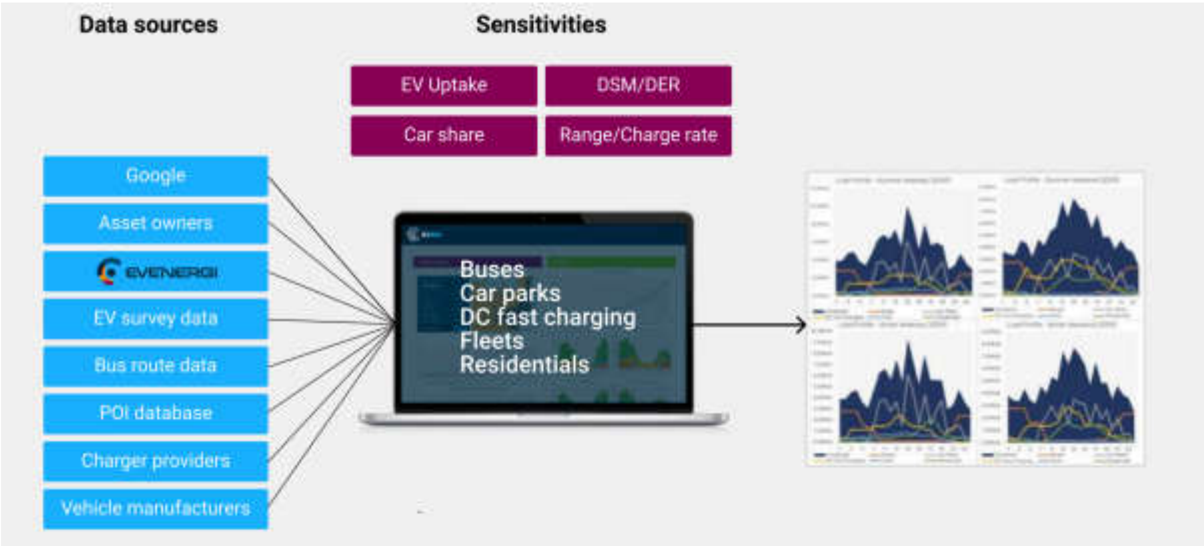


Figure 2: GridFleet™ data architecture

The development of GridFleet™, under the Charge Together Phase 2 program with ARENA was a collaborative process, engaging multiple stakeholders and using a highly iterative development process.

The key contributors to this work alongside Evenergi were Ausgrid and ARENA. As well as contributions from the NSW Department of Planning, NRMA, South Australian Government, Endeavour Energy, AEMO, Macquarie University, Essential Energy and SA Power Networks.

Figure 3: Process applied in the development of GridFleet

This section describes the core functionality of the GridFleet™ power model. It comprises five sub-models or typologies. These are:

1. buses
2. car parks
3. DC fast charging
4. fleet
5. residential

The models of all five typologies produce half-hourly electrical load profiles for summer weekday, summer weekend, winter weekday and winter weekend for 20 forecast years. The seasonality impact is modeled based on average temperature ranges for SA[1]. A typical summer day is modelled at 30°C and witer is modelled at 15°C. An overview of the five GridFleet™ sub-models representing each charging typology for peak demand analysis is provided in the following sections.

[1] http://www.bom.gov.au/climate/averages/tables/cw_023090.shtml

Bus model

The GridFleet™ software first searches the modelled geographical area for locations of all bus depots and the number of buses at each depot The model differentiates public timetabled services and private (charters and coaches) due to different travel patterns. The model only accounts for the charging of electric buses at the depot, based on typical bus travel patterns in SA which are used to create charging profiles.

The peak demand impact on the network is dependent on a number of factors of which the following are the most critical:

1. Number of electric buses at the depot
2. Travel and charging patterns (public/private)
3. Charger capacity distribution
4. Electric bus uptake

Car park model

This typology has been developed to determine the impact of electric vehicle charging in car parks for a specific geographical location. The model firstly detects all of the car parks within an area, determines the number of car spaces in each one and then assigns one of six classifications based on proximity to:

1. Shopping centres
2. Educational institutions
3. Hospitals
4. Local council or privately owned public car parks
5. Street parking
6. Commuter car parks

The six classifications determine the arrival and departure patterns of vehicles and therefore drive charging behaviour which is determined using base charging profiles for each location type. For example, educational institutions are considered to have longer parking times mostly during the day and slower charging. Each classification has its own distribution of charger ratings.

The peak demand impact is dependent on a number of factors of which the following are the most critical ones:

1. Capacity and distribution of chargers at each location type
2. Number of car spaces detected in an area
3. Arrival and occupancy patterns at the carparks
4. EV uptake

DC fast charging model

The DC Fast Charging typology determines the impact of grid peak electrical demand due to the rollout and use of public DC fast chargers for a given geographical area. The fundamental principles of the algorithms in this typology are driven by the charging needs of EV owners. The charging needs are expected to be different for significant urban areas and remote regional areas. Urban charging needs are driven by day-to-day driving, where EV owners will be mainly using the chargers to top up the EV batteries when they don't have access to charging equipment at home or work. While the charging needs of EVs driving in regional areas will focus more on journey enablement. As the driving distances outside metropolitan areas increase and so does the energy consumption of EVs. DC fast chargers will also be utilised by drivers external to the modelled area as they pass through or those visiting from other areas

The model identifies potential charging locations for both geographies.

1. Within urban areas, DC Fast Chargers will be installed in or around certain locations
    a. At fuel stations
    b. In the parking lot of fast food restaurants
    c. Locations near tourist attractions
2. In regional areas, DC Fast Chargers will be installed in or around certain locations
    a. In the parking lot of cafes
    b. In the parking lot of fast food restaurants
    c. At fuel stations
    d. In the parking lot of pubs
    e. Locations near wineries
    f. Locations near tourist attractions

The peak demand impact is fundamentally dependent on probabilistic factors

a. Rollout and availability of DC fast charging infrastructure
b. Percentage of cars on the road with maximum charging capability (50kW, 150kW and 350kW)
c. Number of EVs as a percentage of total cars on the road
d. Visitation profiles for each location type
e. Traffic volumes
f. Percentage of passing EVs stopping to charge

The peak demand impact is dependent on a number of factors of which the following are the most critical ones:

a. Number of potential charging locations in an area (petrol stations, tourist attractions, locations near apartment buildings, etc)
b. Distribution of charger ratings at each location type
c. Usage patterns
d. EV uptake

Fleet model

The fleet typology has been developed to determine the impact of commercial fleet electric vehicle charging. The fleet typology is based on the number of businesses in a geographical area having a fleet of vehicles. This includes commercial pool vehicles, logistics, heavy vehicles and other business-associated vehicles.

The model is broken down into the following subsets of vehicle types:

1. Private vehicles garaged privately
2. Pool vehicles garaged at depot
3. Operational vehicles garaged at depot
4. Operational vehicles garaged privately
5. Heavy vehicles garaged at depot
6. Logistic vehicles garaged at depot

Each of these is considered to have a different arrival and departure profile, energy requirement and charger capacity. These are overlaid to determine the overall charging profile of each fleet.
The model only accounts for charging fleet vehicles at the depot. Fleet vehicles that are charged at home are counted by the residential model. This is achieved by using ABS census data, which captures the number of vehicles garaged at a specific postcode regardless of their registration postcode.

The peak demand impact of this typology is dependent on the following factors:

1. Arrival and occupancy patterns of vehicles at the depot
2. Number of businesses with a fleet in a given geographical area
3. Capacity and distribution of chargers
4. Vehicle class distribution
5. Probability of coincident charging
6. EV uptake

Residential model

The residential typology has been developed to determine the impact of electric vehicle charging on the peak electrical demand due to charging at private dwellings. The fundamental principles of the algorithms in this typology are driven by human driving patterns, that is, the usage patterns of people travelling regularly or occasionally. Distribution curves of vehicle arrivals and departures are overlaid with charging durations based on daily travel requirements and charger ratings to determine charging profiles.

The travel behaviour of EV owners for domestic usage is classified as either regular, or sporadic. The regular behaviour of EV owners have fixed arrival and departure patterns. Their driving distances are also predictable. This makes it easy to estimate the energy requirements and patterns of charging. The sporadic behaviour of EV owners is random in nature. It is hard to determine a pattern in arrival, departure and charging. Therefore, a probability distribution is applied to capture the sporadic behaviour of travel in EV owners. Each of the above categories has its own travel profile and charging demand, which are used to build up aggregated charging profiles.

The model derives the EV uptake for the specific postcode area from top-down EV uptakes for the entire state. Adjustments are made based on three key demographic factors which influence the uptake of EVs.

1. Affluence
2. Dwelling structure, or availability of off-street parking
3. Number of vehicles owned

Affluence is the most sensitive demographic parameter that decides the uptake of EV in the respective postcode. The dwelling structure statistics are used to determine the ease with which an EV charger can be installed at a dwelling. A postcode with a high percentage of separate dwelling structures and high-income earners is likely to have stronger EV uptake, for example. It is assumed that residents of a specific postcode with at least one car in their ownership, are highly likely to buy an EV as their second or third car. These demographics are published by the Australian Bureau of Statistics (ABS). Statewide EV uptake forecasts are adjusted by these scaling factors to determine postcode-based uptakes.

The peak demand impact is dependent on a number of factors of which the following are the most critical ones;

1. Probability of coincident charging
2. Travel patterns
3. Capacity and distribution of chargers
4. EV uptake

GridFleet process

At a high level, the GridFleet™ modelling process consists of four key steps which are shown below.

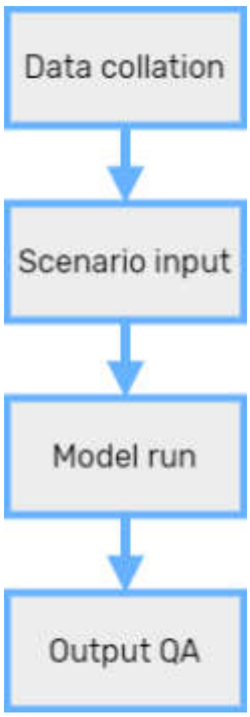


Figure 4: GridFleet™ modelling process flow

The algorithms across all typologies of the models are based on geographical inputs. For example, the residential model uses the number of dwellings in an area as one of its inputs that drives output load curves. As such, the models can be used for geographical areas of any size.

A postcode-based approach, although data-intensive, provides a granular and flexible set of outputs that can be aggregated to form a zone substation level view which can be adjusted at any time if the service area of that substation changes as a result of switching or other modifications. Postcode level modelling also enables the forecaster to zoom in on a particular area and identify potential hot spots in the network.

GridFleet's ability to automate the processing of large volumes of data from multiple data sources was key in achieving very detailed spatial allocation of EV loads across an entire distribution area within a tight delivery timeframe.

Data collation

Inputs were obtained from a large number of data sources and collated in a summary sheet which acts as a central database of all the inputs for the five typology models.

Table 2: Assumptions and inputs			
Bus model			
Key inputs	Source	Collection Method	Manual adjustments
Number of buses (private and public)	[redacted]		
Number of existing electric buses			
Car park model			
Key inputs	Key data sources	Collection Method	Manual adjustments
Location of car parks	[redacted]		

Quantity of car parks			
Number of car parking spaces	[redacted]		
Car park classification	[redacted]		
Number of chargers installed			
DC fast charging model			
Key inputs	**Key data sources**	**Collection Method**	**Manual adjustments**
Locations of POIs for journey enablement (cafe, fast food, fuel station, pub, winery, tourist attractions)	[redacted]		
Locations of POIs for urban areas (fast food, fuel station, tourist attractions)			
Number of chargers installed			
Traffic volume for highway charging			
Google popular times			

[redacted]

Fleet model			
Key inputs	Key data sources	Collection Method	Manual adjustments
Total number of businesses	[redacted]		
Percentage of businesses having fleet			
Number of vehicles per fleet			

Residential model			
Key inputs	Key data sources	Collection Method	Manual adjustments
Demographics - median income, employment, dwelling structures and vehicle ownership	[redacted]		
Vehicle registrations			
Number of electric vehicles per fleet			

Scenario input

To model each of the scenarios, key escalators such as EV uptake, Demand Side Management (DSM), population growth and others need to be set equally across the five typology models. This is done via a central scenario input sheet and an automation script that applies the data to the models.

The model then ran for 339 postcodes, using 280 inputs per postcode, across five models. This is done by running an automation script, which takes the data for a postcode, enters it into the models, retrieves the output from the models, then repeats this for the remainder of the postcodes. Once all the outputs are extracted (i.e. summer weekday, summer weekend, winter weekday, winter weekend for all 339 postcodes), these outputs are transferred to the consolidated output sheet in Excel.

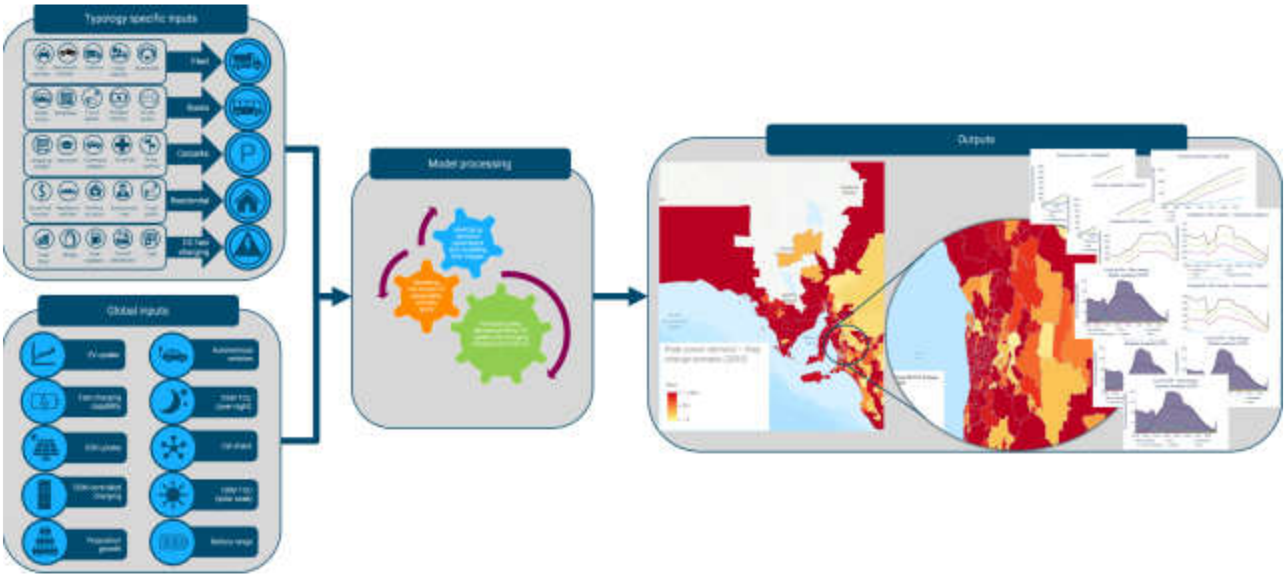


Figure 5: Model process flow diagram

Output QA

To ensure that the results obtained were within expected bounds, the following quality assurance process was carried out.

Table 3: Data QA process	
Description	**Intent**
Maximums and minimums	To find postcodes with peaks over 5MW or that had zeros across all years. When found, each postcode was manually reviewed and checked whether the outputs were consistent with number and types of physical locations in the postcode.
Inputs correlate with outputs	To ensure that the script had run correctly and input data for a given postcode matches the output that the script obtained. This was donemanually.
Power output to quantity of chargers	Backsolving total megawatt demand to a quantity of chargers using an average charger rating and checking to see if this correlates with the intended number for a postcode area.

Number of vehicles modelled	The number of vehicles modelled is checked against the number expected across the SAPN region.
Energy consumed per vehicle	The total energy (kWh) for each of the typologies was checked against the number of vehicles modelled and verified to be within acceptable bounds when translated to kilometres driven per day.
After diversity contribution per vehicle	The after-diversity peak demand contribution per vehicle (kW/vehicle) in each model typology is verified against expected metrics. The kW/vehicle ratio is expected to remain consistent for all years. It will vary over years due to two factors, the EV uptake and the coincident charging factor.
Known large loads	Postcodes that are known to have a bus depot or have a potential highway DC fast charging site were checked to ensure they contained these loads.
Load profiles	Outputs were plotted for year 2030 for each of the typologies and their profile was checked against each of the models verifying their charging profile and overall peak.
Logical checks of geographical areas	A sample of geographical areas is checked manually for validity. This is done by zooming in on an area and checking for actual locations where chargers can be installed, then verifying this with the model outputs.
Aggregated energy demand forecast	The aggregated energy demand forecast for the entire SAPN's network is compared with SA's energy demand forecast due to EV uptake.
Hot spots on the map	The yearly maximum demand for individual typologies and the aggregated power demand for the entire network by postcode are plotted on ArcGIS map. The hotspots are identified and validated with the inputs for respective postcodes.

Scenarios modelled

To account for different EV charging factors and their combinations, a wide variety of scenarios were modelled for SAPN's network. Factors that will impact the charging demand from EVs are:

- EV uptake: AEMO has supplied five EV uptake forecast scenarios.
- Day type: travel patterns differ between the weekday and the weekend.
- Seasonality: energy efficiency and travel patterns of EVs differ between summer and winter.
- Time of Use (TOU) tariff uptake: network operators incentivise energy consumers to utilise energy at specific times of the day, to avoid coincident peak power demand at other times of the day. Three TOU schemes were modelled to capture a range of possible TOU tariff adoption scenarios.
- Peak day scenario: EV charging demand is expected to peak when the majority of residential EV owners tend to charge in the same time band after returning from long journeys, or in peak holiday locations. For fixed route vehicles such as buses the charging demand is increased on hot summer days due to air conditioning load.

EV uptake

The following five EV uptake scenarios were modelled, a detailed breakdown of uptakes by vehicle type is provided in Appendix A.

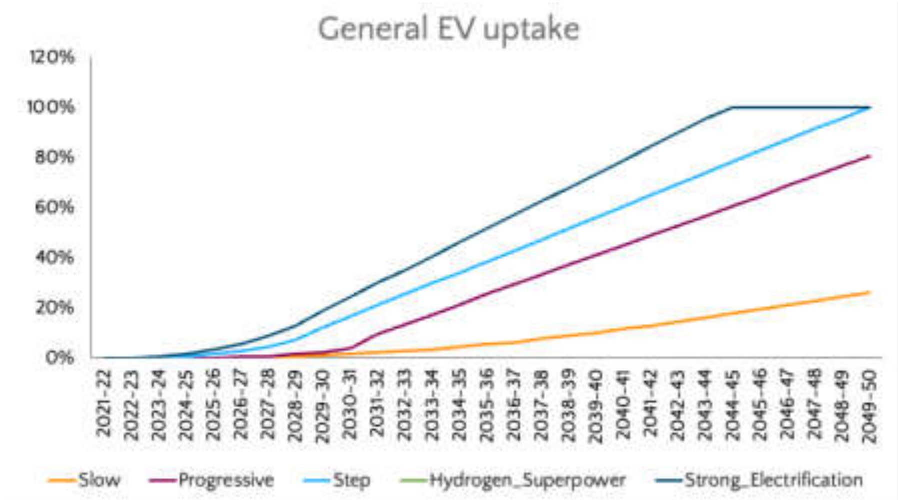


Figure 6: AEMO EV uptake scenarios

The step change scenario is now widely considered by stakeholders as the likely scenario for EV adoption in Australia. The Federal Government's emissions reduction targets and AEMO's Integrated System Plan (ISP) are aligned with this uptake scenario.

Day type

Weekday and weekend travel patterns of vehicles typically vary for all classes of vehicles. The table below provides an overview of the key differences between weekday and weekend travel patterns by typology. This data was collated from Evenergi's modelling of various real-world fleets, as well as travel survey data for residential vehicles.

Table 4: Weekend versus weekday travel patterns

Typology	Weekday	Weekend
Bus	Bus duties are more intense on weekdays, resulting in greater distance travelled and more buses on the road.	Distance travelled by buses on weekends is around 80% that of weekdays, as well as less buses on the road.
Car park	Occupancy ratio of carparks is consistent during the day on	Occupancy ratio is slightly higher during early hours of the day on

	weekdays.	weekends.
DC fast charging	These are dependent on location type. Popular times data was obtained for all location types likely to host DC fast chargers, such as petrol stations, tourism attractions, wineries and others.	
Fleet	Fleet vehicles experience heavier duties on weekdays. Pool vehicles will typically be garaged at depots or offices during the day. Logistics and heavy vehicles will travel higher kilometres.	Privately garaged vehicles do not charge at depots on the weekends. Most fleet vehicles have lower duties on weekends.
Residential	The travel patterns during the week are reflective of consistent and repeat travel from/to work.	Travel patterns are more sporadic during the weekends and therefore spread more throughout the day.

Seasonality

Seasonality has different impacts on different vehicle classes and use cases. In most cases it is due to higher energy consumption due to air conditioning, however in some instances travel patterns will also change for different seasons. An overview of seasonality impacts modelled is provided in the table below.

Table 5: Seasonality impacts		
Typology	Summer	Winter
Bus	The scheduled distances remain the same for buses. However, energy consumption increases due to additional cooling needs.	The energy efficiency is slightly higher compared in winter due to additional heating needs.
Car park	The occupancy of carparks is higher in summer due to extended daylight hours.	The occupancy patterns are consistent during the day.
DC fast charging	The traffic volumes are higher in summer due to extended daylight hours.	The traffic volumes are lower in winter but the charging needs are high due to additional heating needs.
Fleet	Energy consumption in fleets is higher due to additional cooling demand.	Energy needs are increased due to additional heating needs in winter.
Residential	Travel distances increase in summer due to increased daylight.	Energy needs are increased due to additional heating needs.

To obtain autumn and spring profiles the summer and winter profiles for each typology can also be multiplied by the following scaling factors:

Table 6: Scaling factors for autumn and spring	
Season	Scaling factor
Autumn	1.02 x summer
Spring	0.91 x winter

TOU tariff uptake

As the models have different commercial drivers for DSM, a separate set of escalators was applied to each of them. It is expected that energy tariffs will have a significant influence on the charging habits of EV owners, both residential and commercial, in order to prevent escalating operational expenses.

Initial scenarios were run with the following assumptions:

- Given the significant loads brought on by EV charging at bus depots and the financial incentives to control energy costs, it is estimated that 70% of all buses will charge during off-peak load times in accordance with established TOU tariffs. This will grow at 10% annually until 90% of the buses charge during the off-peak load hours. To meet the schedule requirements, 10% of the buses will still need to charge during peak load times.

- Similarly, 70% of all fleet vehicles will charge during off-peak load times in accordance with the established TOU tariffs. This will grow at 10% annually until 80% of the fleet vehicles charge during the off-peak load hours. To meet schedule requirements, 20% of the vehicles will still need to charge during peak load times. However, the adoption of TOU tariffs for residential consumers mainly depends on the uptake of smart meters. It is assumed that 30% of all residential vehicles will charge during off-peak load times in accordance with the established TOU tariffs. This will grow at 10% annually until 80% of the residential vehicles charge during off-peak load hours.

- On the public charging front, EV drivers plugging in at car parks and DC fast charging locations will expect this to be an ‘on-demand’ service, therefore shifting or controlling the timing of charging is not possible.

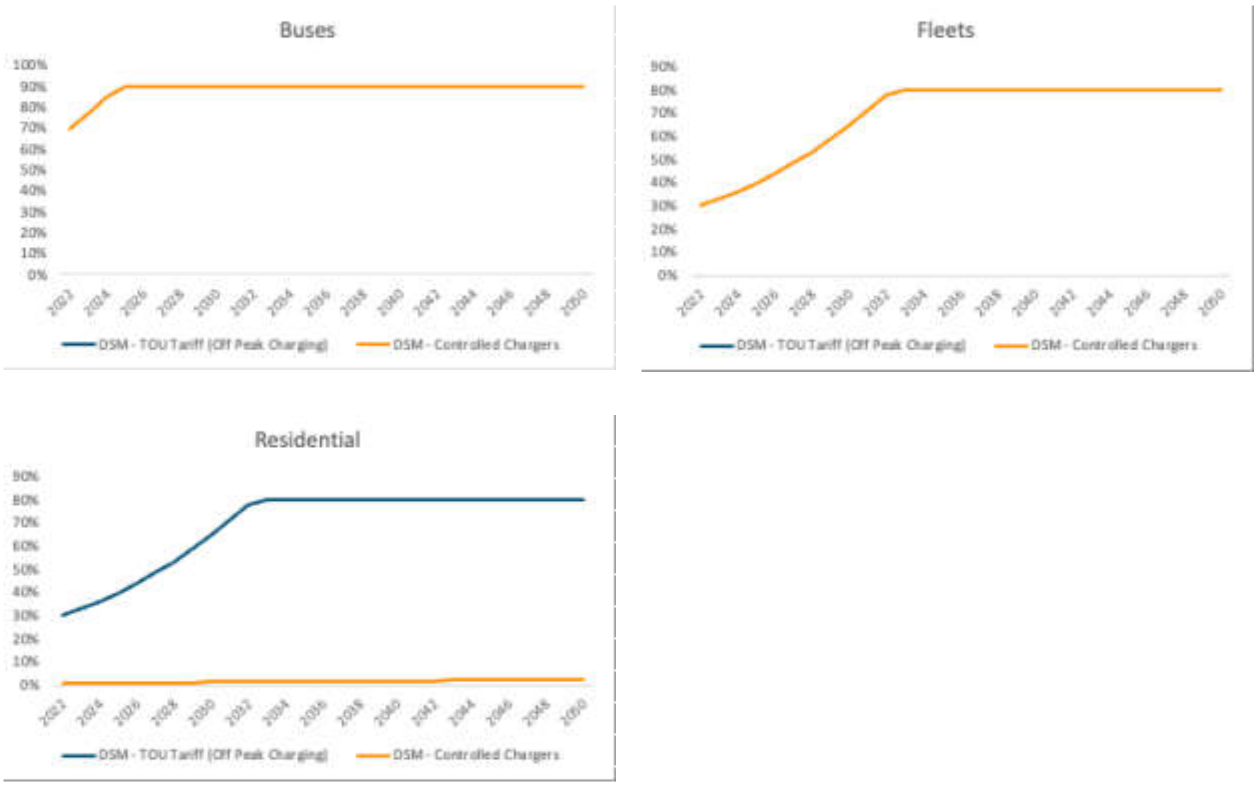


Figure 7: DSM assumptions

However, it can be assumed that due to the flexible nature of EV charging and the large amount of energy required that most EV owners will adopt a TOU tariff soon after purchasing the vehicle. The charging behaviour can be broadly categorised into three scenarios.

- **Day-time charging**: There has been a recent introduction of solar sponge tariffs, whereby network operators encourage daytime energy consumption. The purpose of these tariffs is to drive consumption behaviour to maximise utilisation of solar power generation and reduce impacts of minimum demand.

- **Night-time charging**: Due to naturally low energy demands overnight, network operators may also continue to provide traditional off peak night time tariffs which EV drivers can use to minimise costs.
- **Convenience charging**: Some EV owners will charge when it is most convenient for them since they need to travel and won't be swayed by lower energy rates that provide cost savings.

Since it is difficult to predict the yearly adoption of each form of charging behaviour with accuracy over a 20 year horizon, it was decided in collaboration with SAPN that a bookend scenario analysis would provide a risk-based approach . To illustrate the extreme and moderate use cases of EV charging behaviour, three TOU adoption scenarios were modelled for each of the five AEMO scenarios.

Table 7: TOU scenarios

TOU scenarios	TOU scenario 1[4]	TOU scenario 2	TOU scenario 3
Night-time charging	55%	70%	14%
Day-time charging	31%	16%	16%
Convenience charging	14%	14%	70%

Peak day

The maximum demand day scenario is aimed at analysing the impact of EV charging on a hot summer day that coincides with a public holiday. A hot summer day is defined as 45°C. It is assumed that most EV owners would be reaching their home with an empty EV battery after long trips and within a similar time window between 3pm and 6pm.

Output summary

This section summarises the key insights obtained from the results of the power modelling. For the given set of inputs defined for each typology, the modelling considered respective escalators to produce results for each scenario, as described above. The results for all five charging typologies are generated by the model for each postcode in SAPN's service area and provided as 'csv' files. The 'csv' files contain the postcode-wise load profiles of all typologies at half hourly intervals for 20 years. To capture the effect of charging demand due to seasonal variations, the model also forecasts the power demand profiles for representative summer weekday, summer weekend, winter weekday and winter weekend days.

[4] https://electricvehiclecouncil.com.au/wp-content/uploads/2022/08/Home-EV-charging-2030.pdf

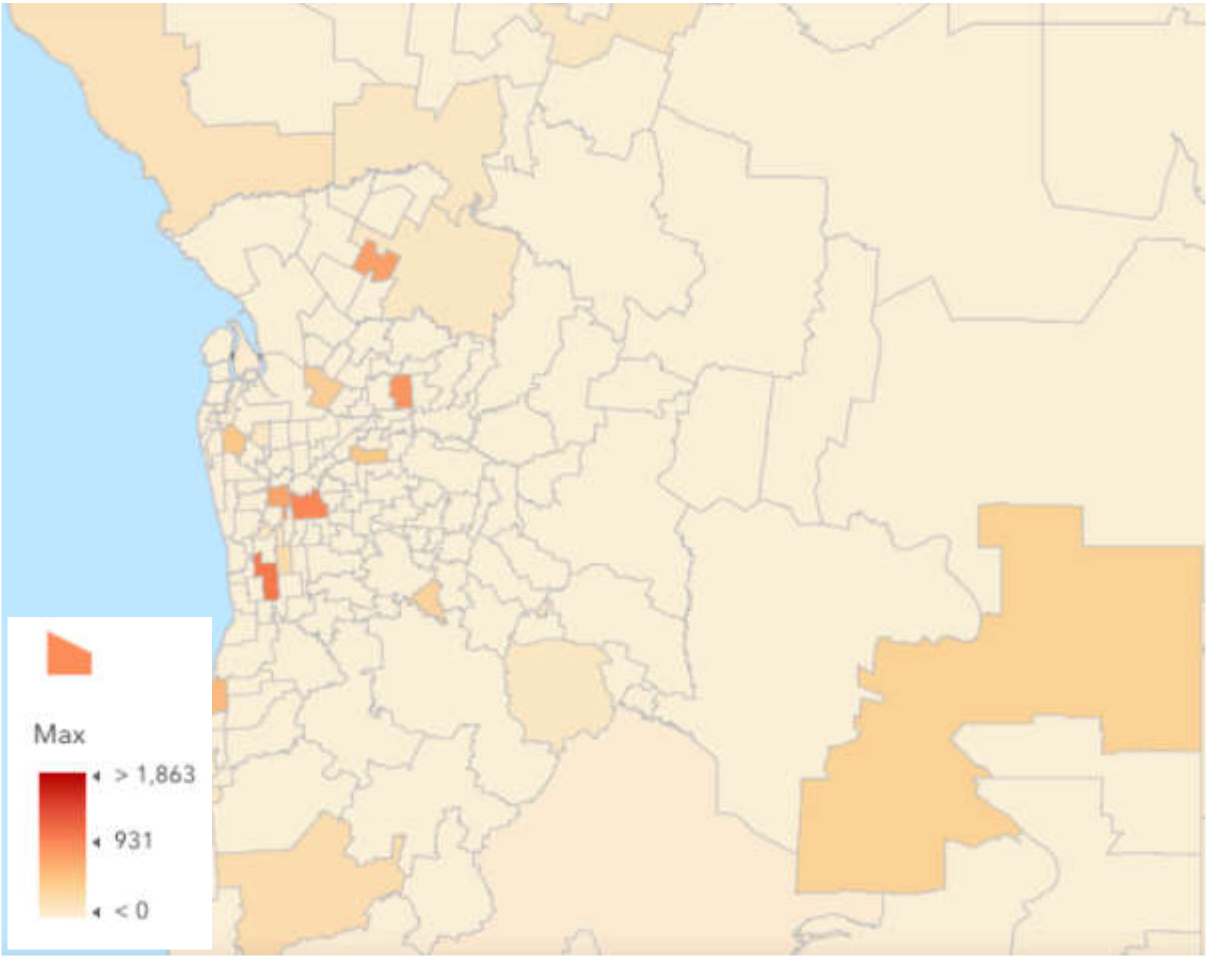
Detailed load profiles and vehicle uptake results were provided as Microsoft Excel sheets, the key highlights for each of the five typologies are presented in the following sections. Each one discusses the spatio-temporal distribution of the power demand for a representative year, the annual forecast of load growth and a comparison of the peak demand day with normal day for all TOU scenarios.

All heatmap outputs below are from the AEMO step change EV uptake scenario of modelling and provided as typical. The concentration of loads on the network will occur relatively the same across different scenarios, albeit with different timing.

Impact of electric bus uptake on SAPN network

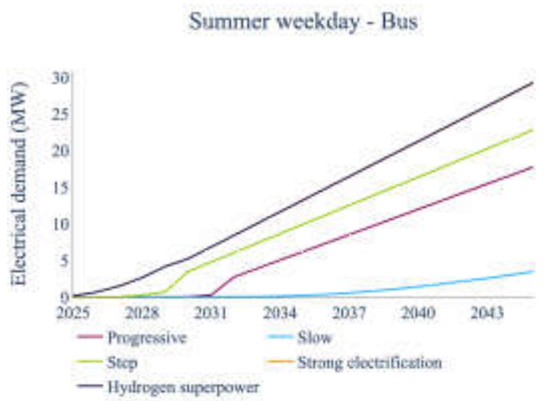
This section presents the key highlights of the bus modelling. The heatmap presents the postcodes within the significant urban area (SUA) of Adelaide. As most of the postcodes do not host a bus depot, so there is no impact of electric bus charging. The maximum power demand of 1.3 MW in 2035 is forecasted at 5043 postcode on a winter weekday.

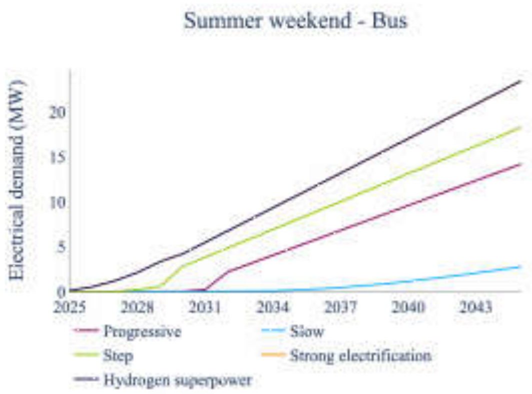
Buses: Spatiotemporal peak power demand for step change EV uptake scenario in 2035

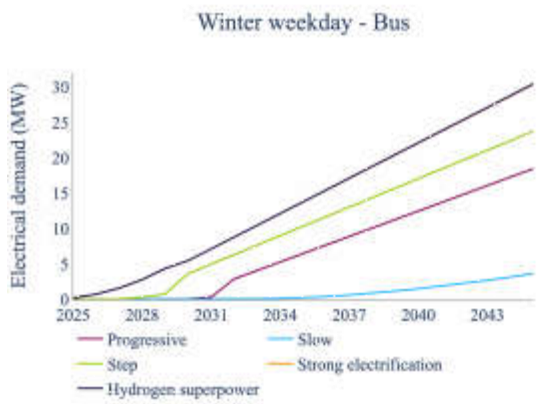


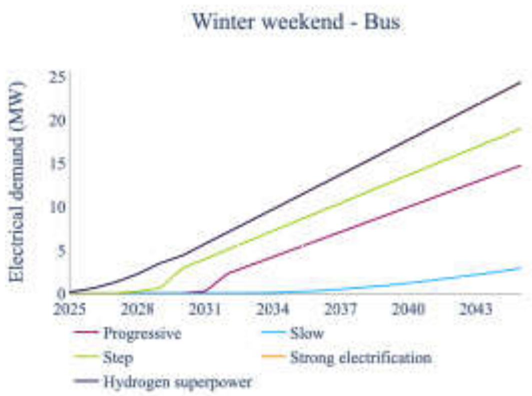
The following graphs present the forecast of annual peak power demand due to electric bus charging across the entire network.

Buses: Annual growth in peak power demand



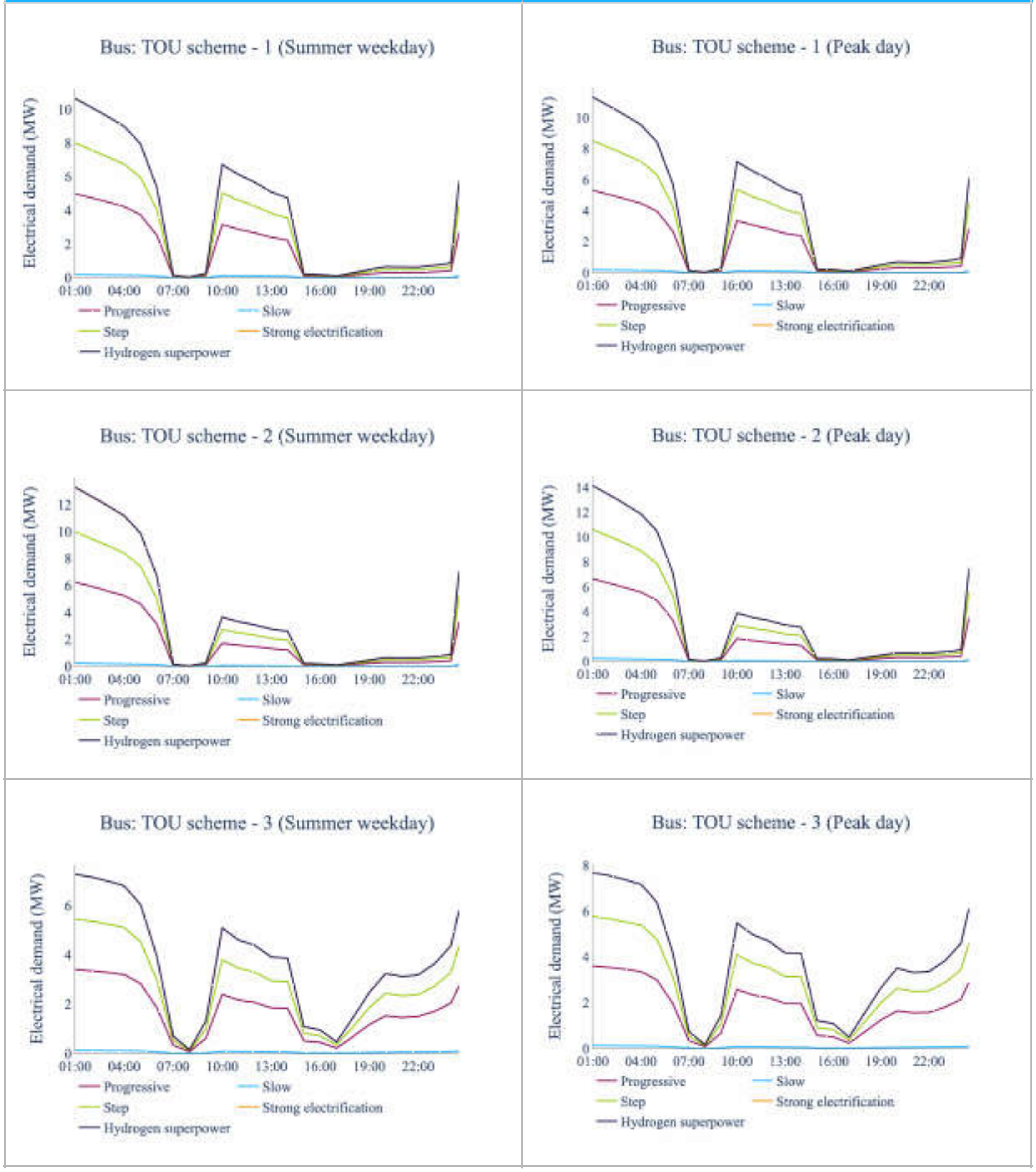






The following charts present a comparison between a normal day and a peak demand day. As defined previously, it is expected that the energy demand will rise on a peak demand day due to additional heating or cooling needs. A comparison is presented for all three TOU scenarios.

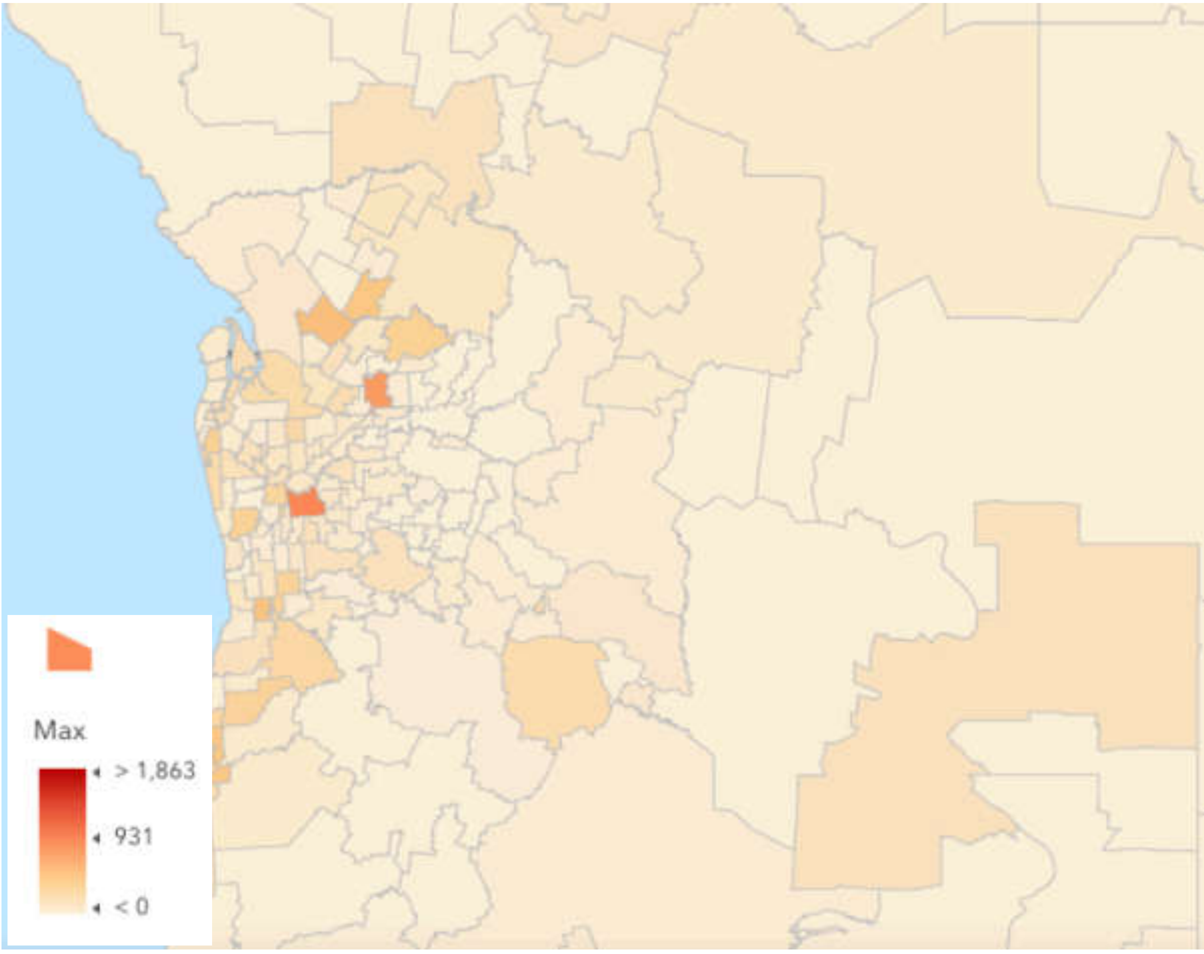
Buses: Comparison of peak demand day and summer weekday for all TOU scenarios in 2035



Impact of public charging at car parks on SAPN network

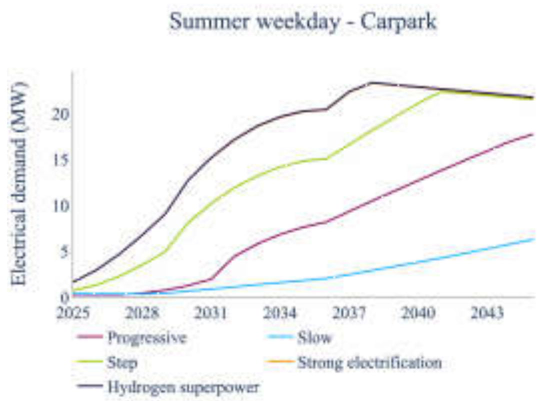
This section presents the key highlights of the public charging at carparks. The heatmap presents the postcodes within the significant urban area (SUA) of Adelaide. The charging demand at carparks is low, as it is expected that majority of the chargers at carparks will be AC powered with majority of chargers rating between 7.6kW and 22kW. The maximum power demand of 1.0 MW in 2035 is forecasted at 5000 postcode on a winter weekday.

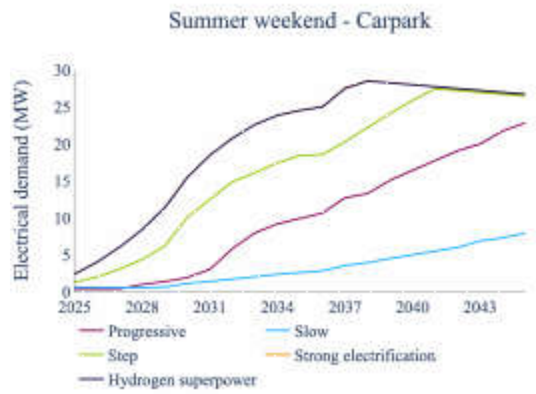
Carparks: Spatiotemporal peak power demand for step change EV uptake scenario in 2035

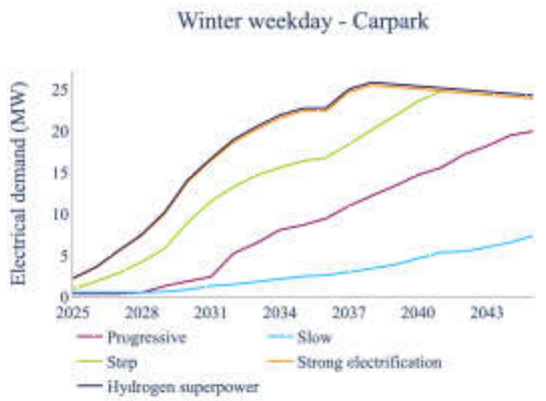


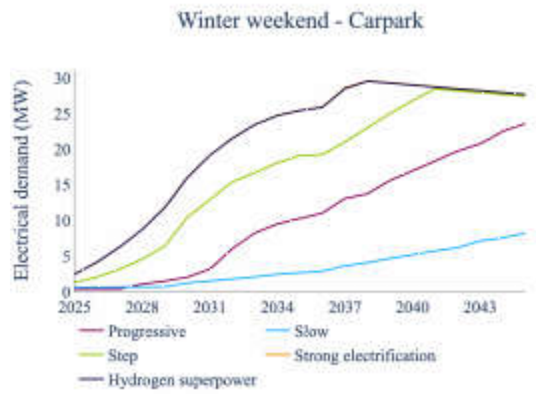
The following graphs presents the forecast of annual peak power demand due to public charging of EVs at carparks.

Carparks Annual growth in peak power demand





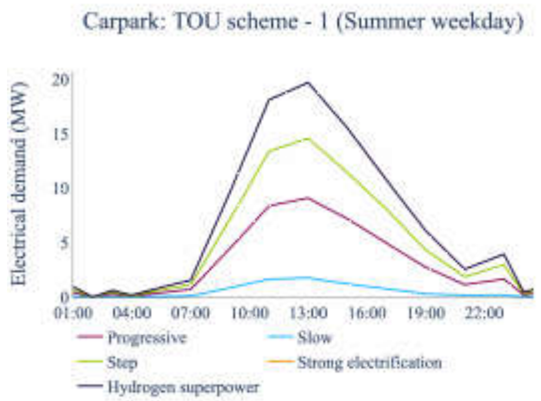


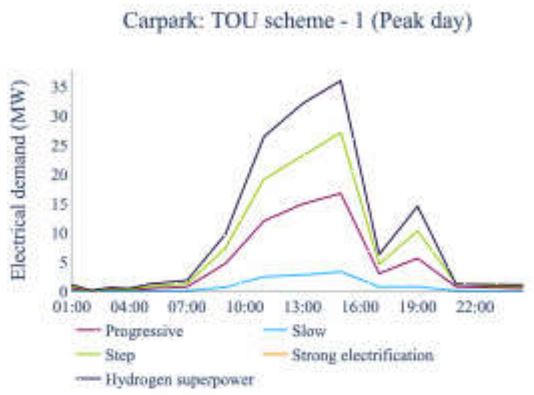


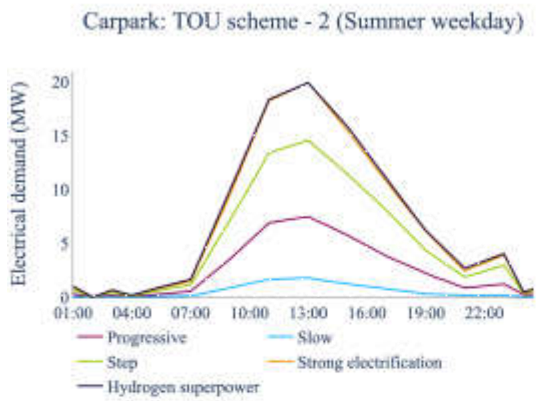
It should be noted that the peak demand at parking lots gradually decreases in the forecasts later years for faster EV uptake adoption scenarios. This is due to the fact that coincident charging is predicted to decline as car sharing and to a lesser extent autonomous vehicles become more widely used because those vehicles will charge more frequently for relatively brief periods of time to recharge. Another assumption about parking lots is that a maximum of 30% of car spaces will have chargers. This is to account for supply constraints and prohibitive costs of installing infrastructure to every space. As soon as this cap is reached, the number of chargers remains constant, but the coincident charging factor falls by 1% annually.

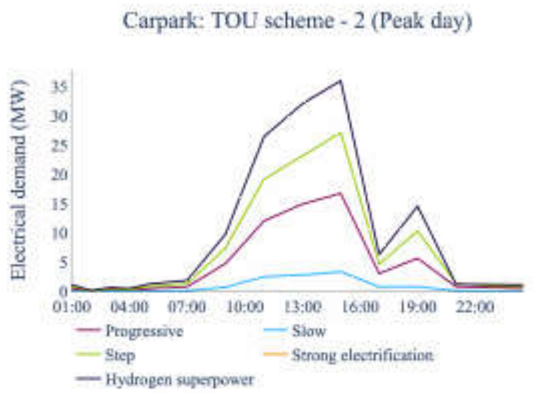
The following charts present a comparison between a normal day and a peak demand day. As defined previously, it is expected that the energy demand will rise on a peak demand day due to additional heating or cooling needs. A comparison is presented for all three TOU schemes.

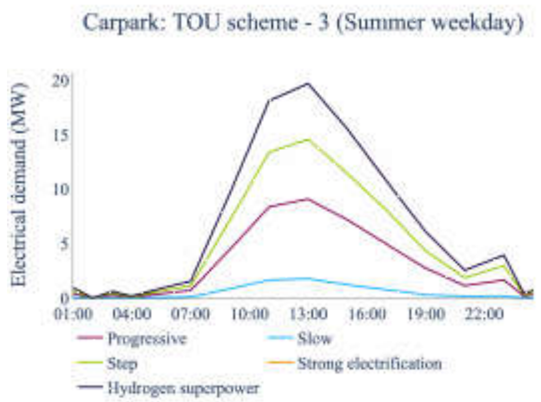
Carparks: Comparison of peak demand day and summer weekday for all TOU schemes in 2035

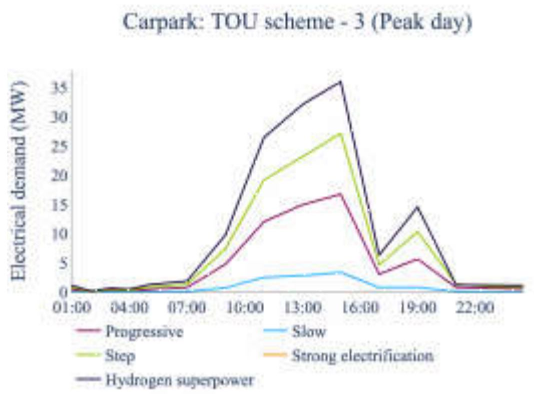








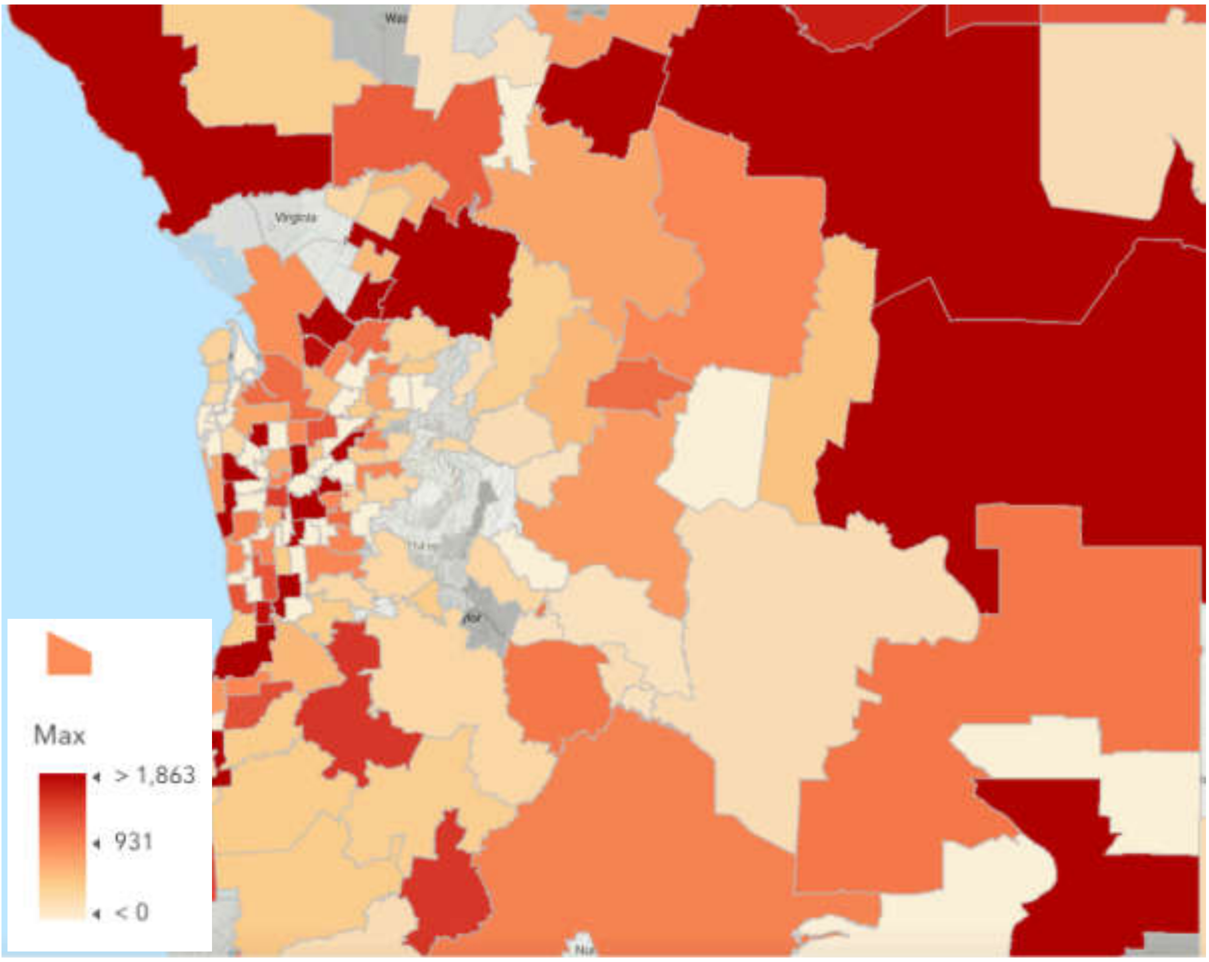




Impact of DC fast charging on SAPN network

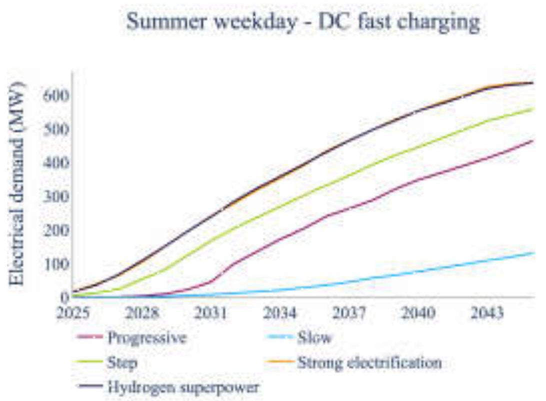
This section presents the key highlights of the public charging at DC fast charging stations. The heatmap presents the postcodes within the significant urban area (SUA) of Adelaide. The charging demand at DC fast charging stations is high, as it is expected that majority of the chargers at DC fast charging stations will be powered between 50kW and 150kW. The maximum power demand of 5.8 MW in 2035 is forecasted at 5267 postcode on a summer weekday.

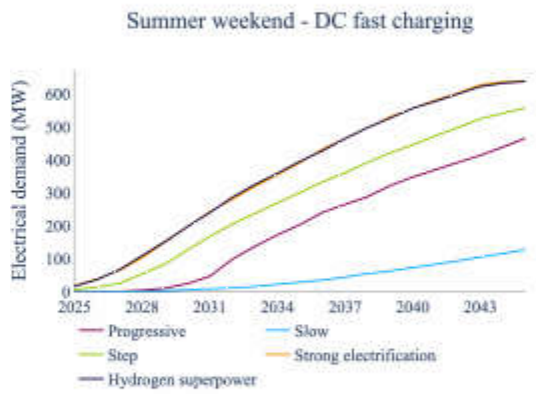
DC fast charging: Spatiotemporal peak power demand for step change EV uptake scenario in 2035

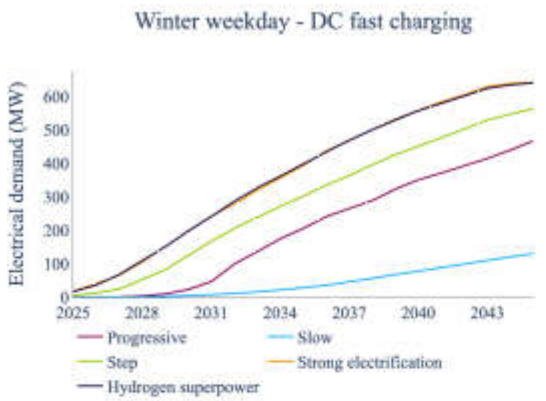


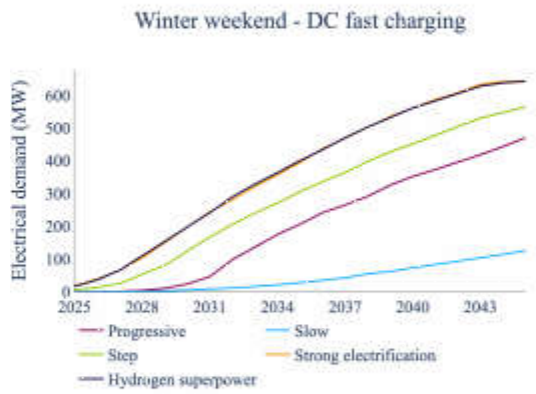
The following graphs presents the forecast of annual peak power demand due to charging of EVs at DC fast charging stations.

DC fast charging: Annual growth in peak power demand



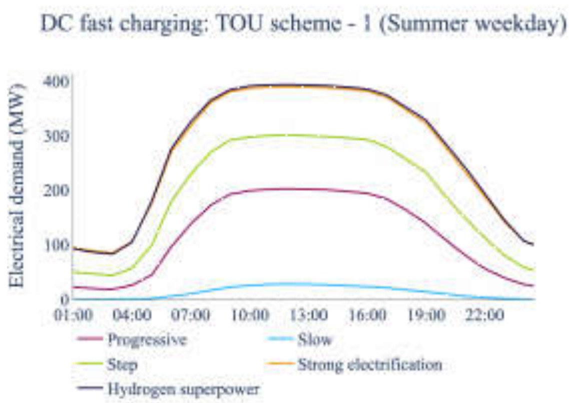


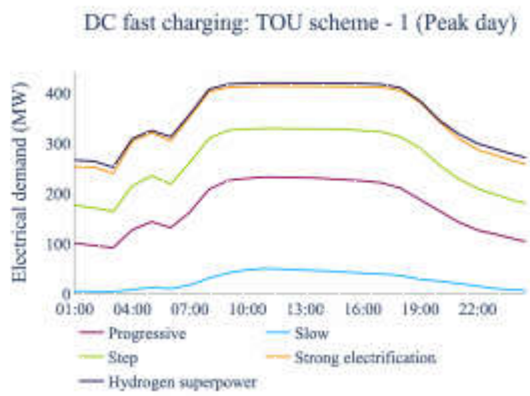


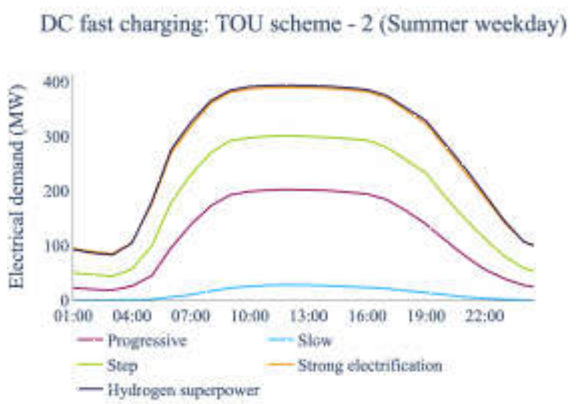


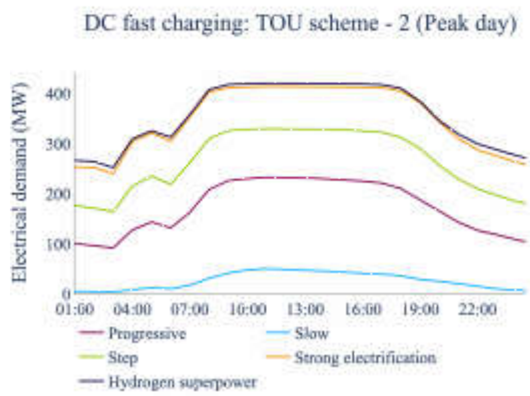
The following charts present a comparison between a normal day and a peak demand day. As defined previously, it is expected that the energy demand will rise on a peak demand day due to additional heating or cooling needs. A comparison is presented for all three TOU schemes.

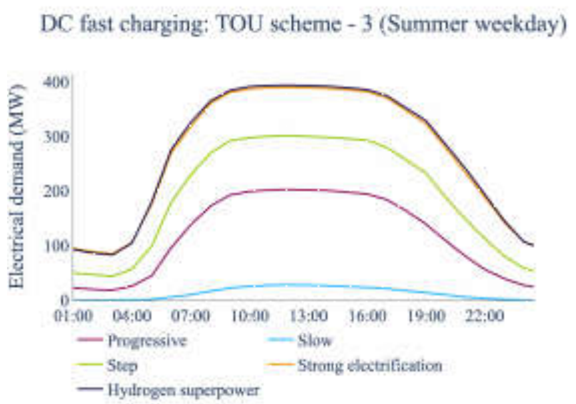
DC fast charging: Comparison of peak demand day and summer weekday for all TOU schemes in 2035

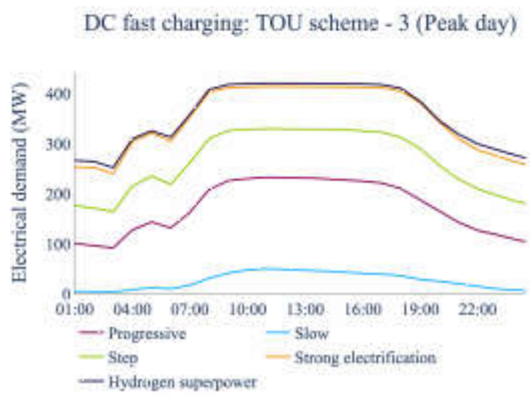








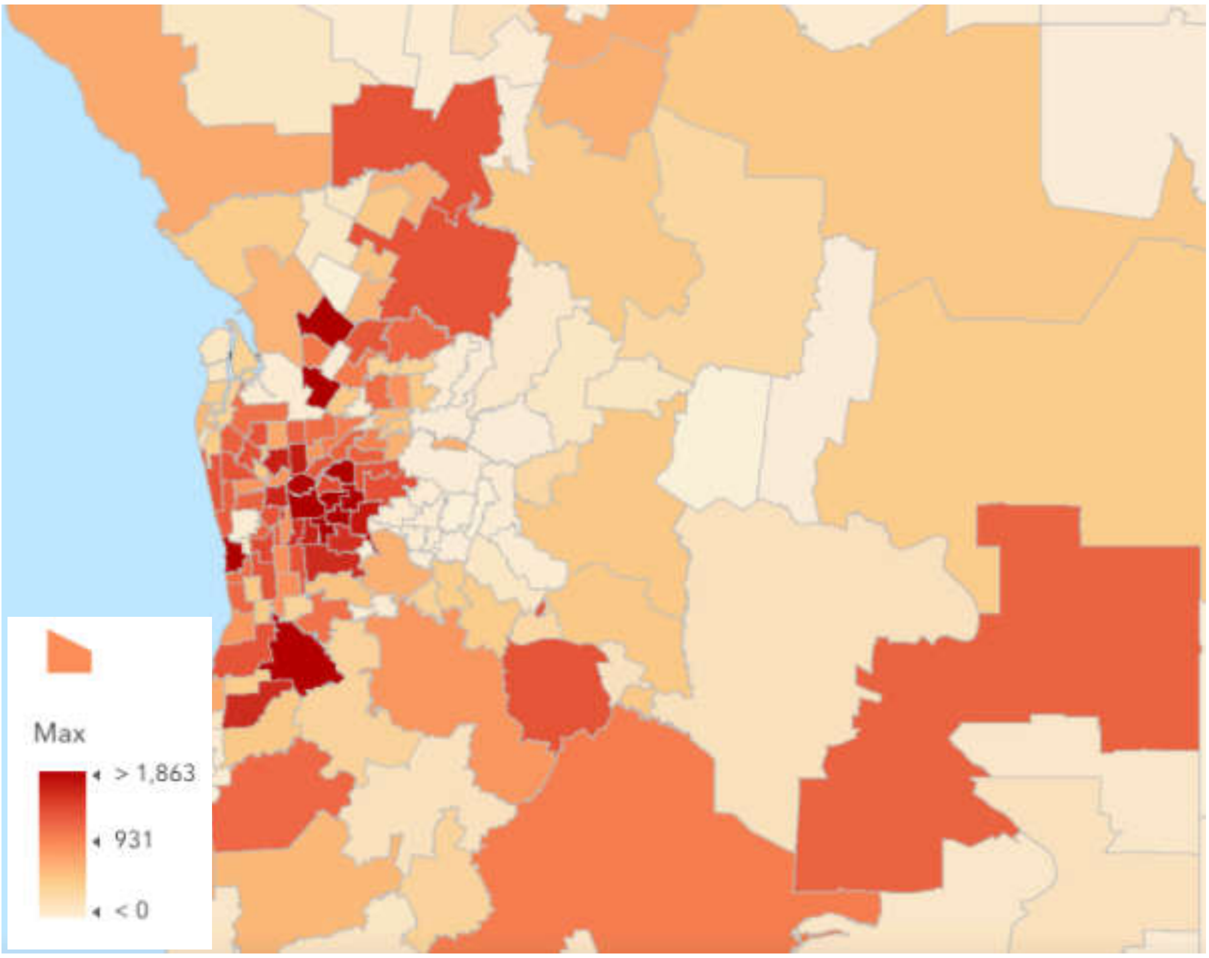




Impact of electrified fleets on SAPN network

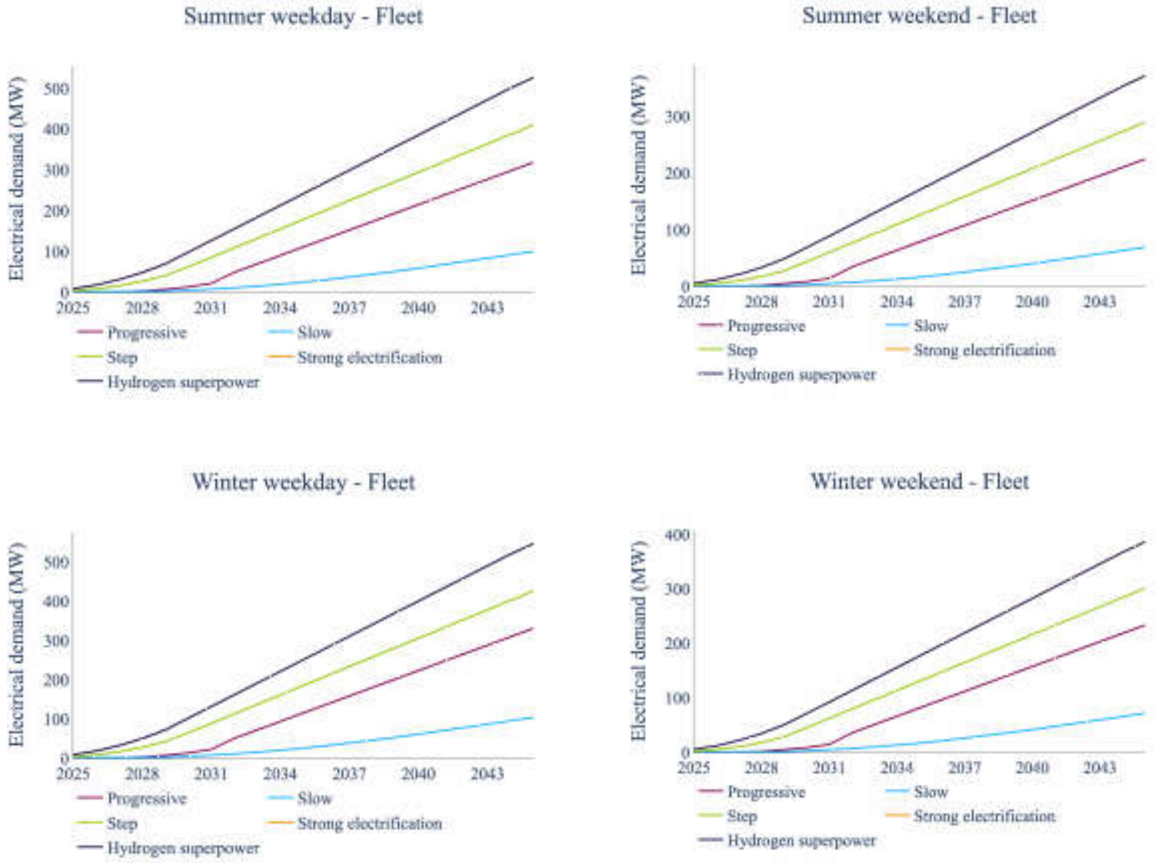
This section presents the key highlights of the EV fleet charging at private depots. The heatmap presents the postcodes within the significant urban area (SUA) of Adelaide. The charging demand at fleet depots is high, as there are large number of businesses and it is expected that majority of the chargers at EV fleet depots will be powered between 50kW and 150kW. The maximum power demand of 11.1 MW in 2035 is forecasted at 5000 postcode on a winter weekend.

Fleet: Spatiotemporal peak power demand for step change EV uptake scenario in 2035



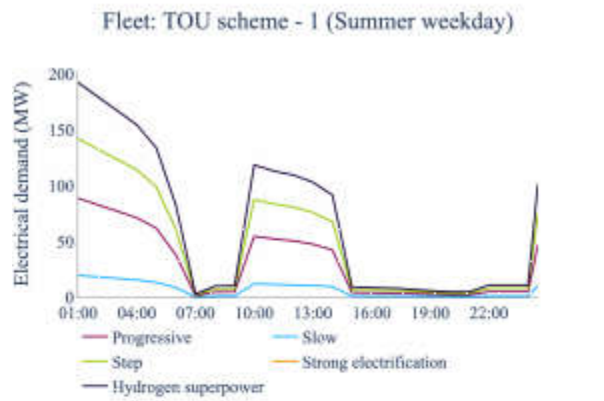
The following graphs presents the forecast of annual peak power demand due to charging of EV fleets at private depots.

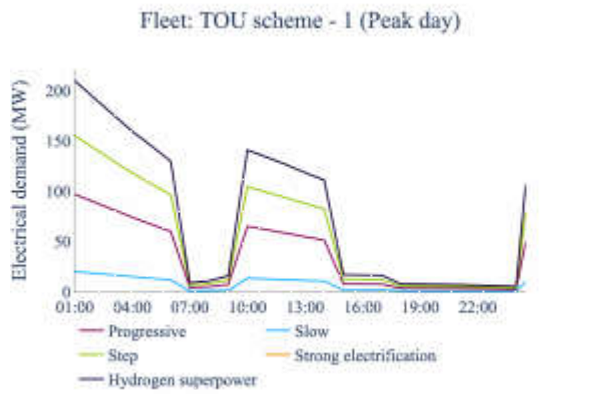
Fleet: Annual growth in peak power demand

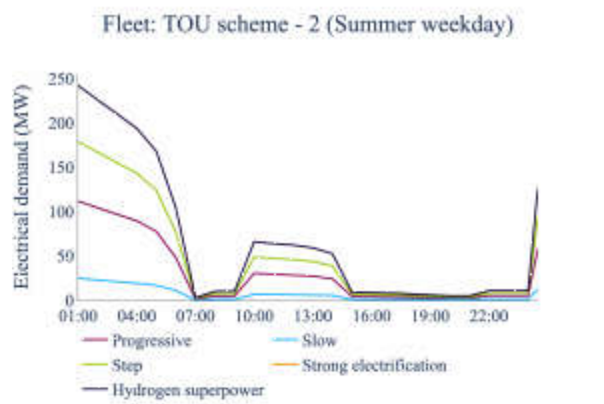


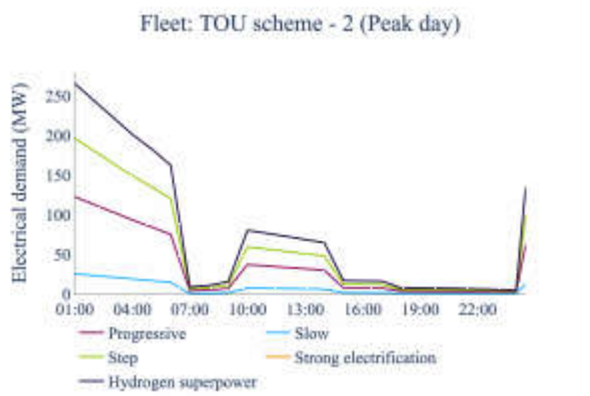
The following charts present a comparison between a normal day and a peak demand day. As defined previously, it is expected that the energy demand will rise on a peak demand day due to additional heating or cooling needs. A comparison is presented for all three TOU schemes.

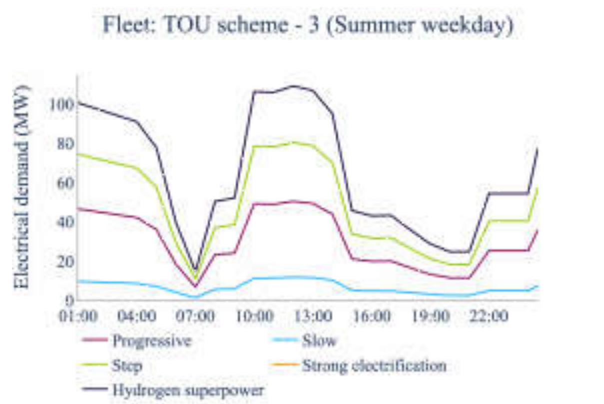
Fleet: Comparison of peak demand day and summer weekday for all TOU schemes in 2035

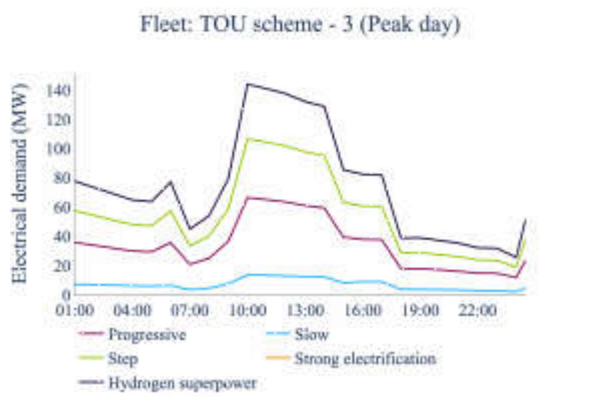








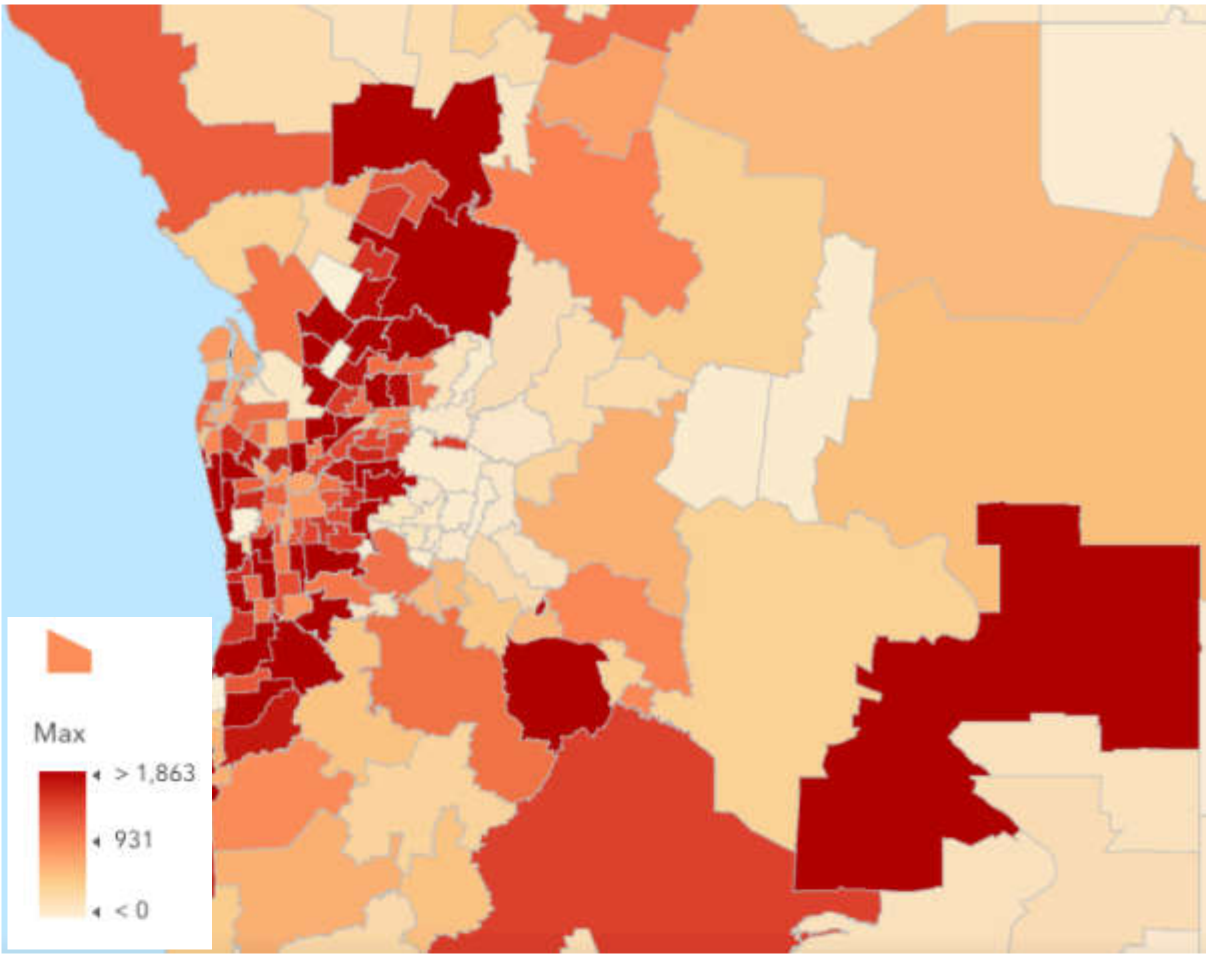




Impact of residential EV charging on SAPN network

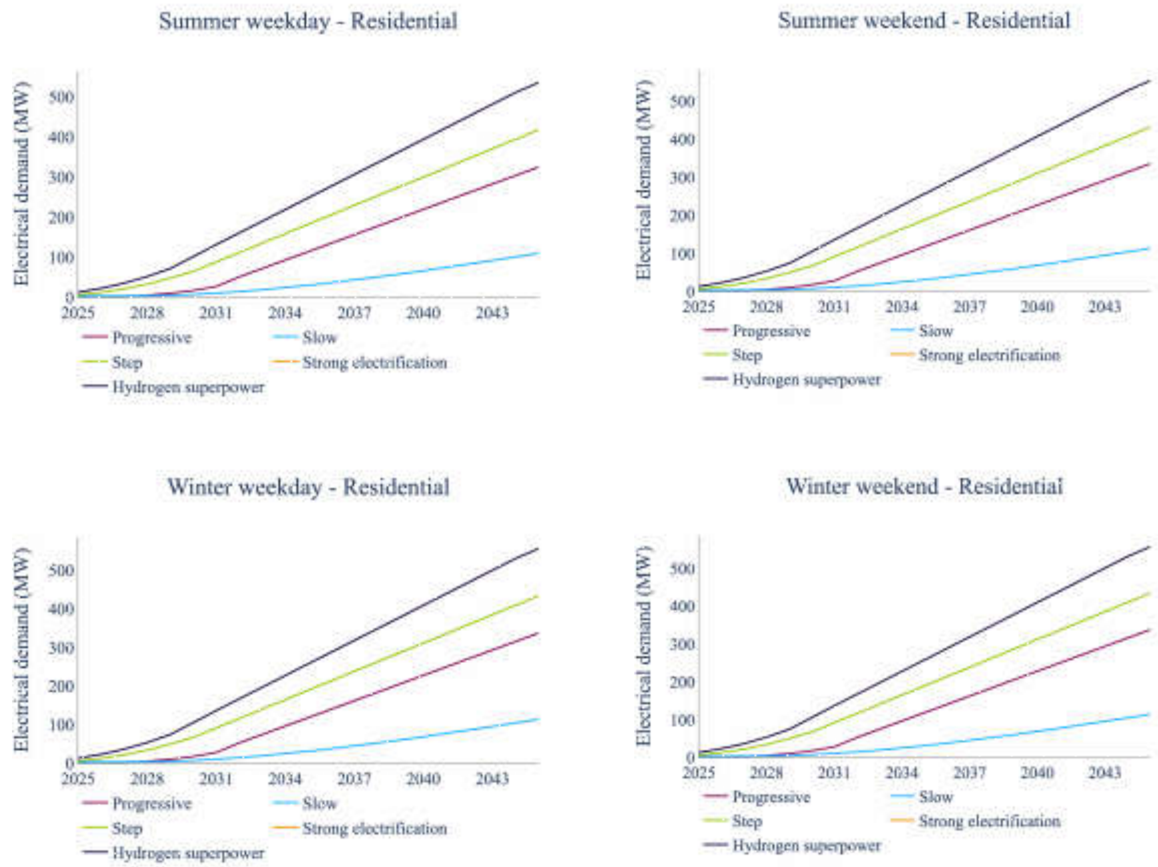
This section presents the key highlights of the EVs charging at home. The heatmap presents the postcodes within the significant urban area (SUA) of Adelaide. The charging demand at homes is high, as there are large number of houses that can afford an EV. It is expected that majority of the houses will have a single phase connection and the chargers installed at homes will be powered between 3.6kW and 7.2kW. The maximum power demand of 4.9 MW in 2035 is forecasted at 5159 postcode on a winter weekday.

Residential: Spatiotemporal peak power demand for step change EV uptake scenario in 2035



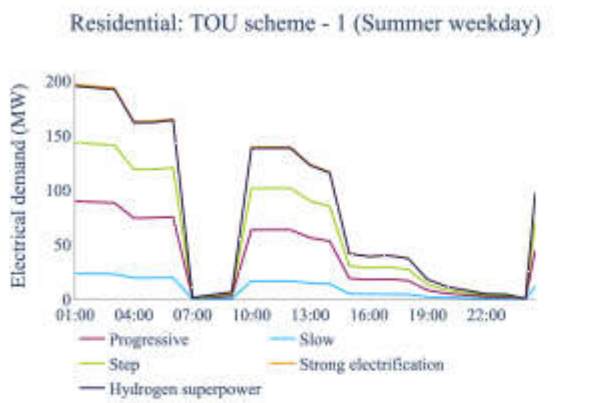
The following graphs presents the forecast of annual peak power demand due to charging of EVs at home.

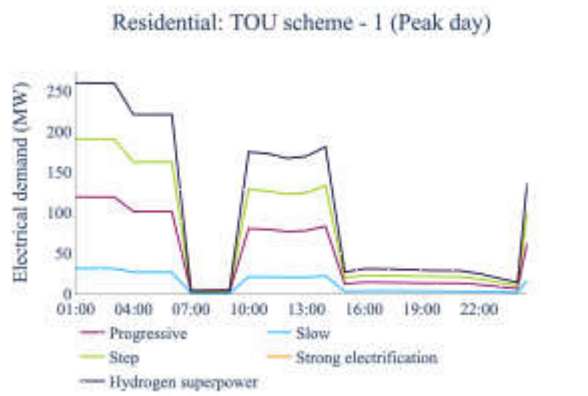
Residential Annual growth in peak power demand

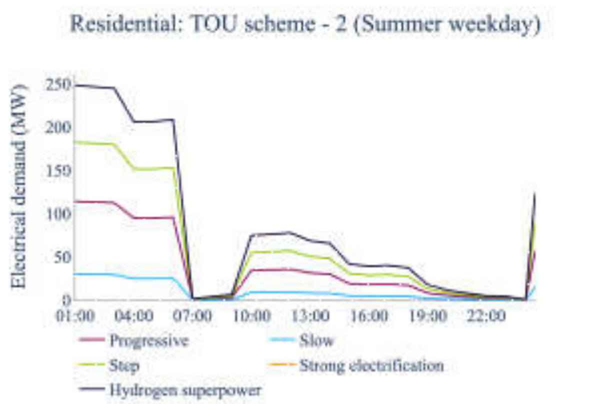


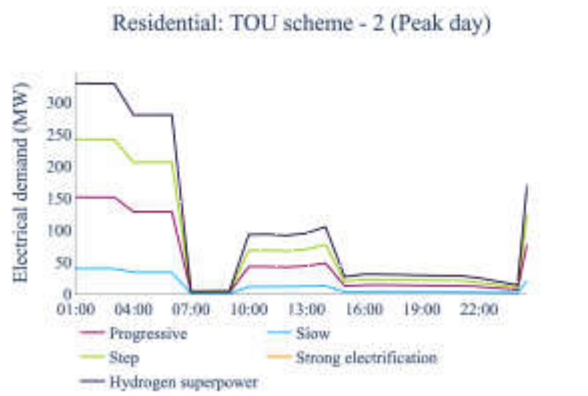
The following charts present a comparison between a normal day and a peak demand day. As defined previously, it is expected that the energy demand will rise on a peak demand day due to additional heating or cooling needs. A comparison is presented for all three TOU schemes.

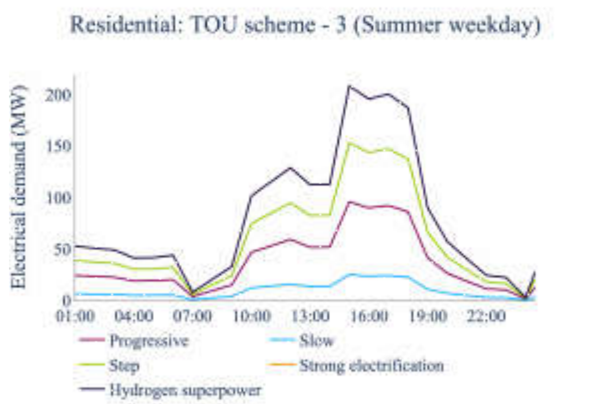
Residential: Comparison of peak demand day and summer weekday for all TOU schemes in 2035

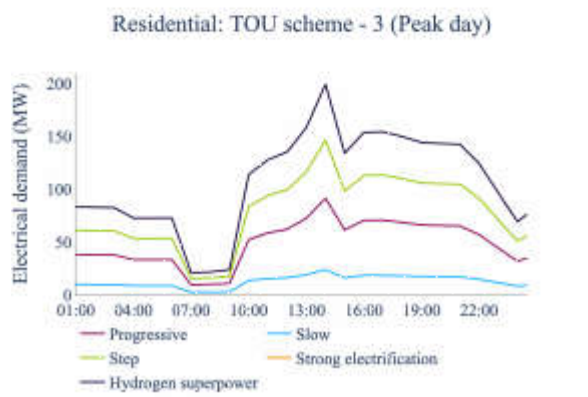








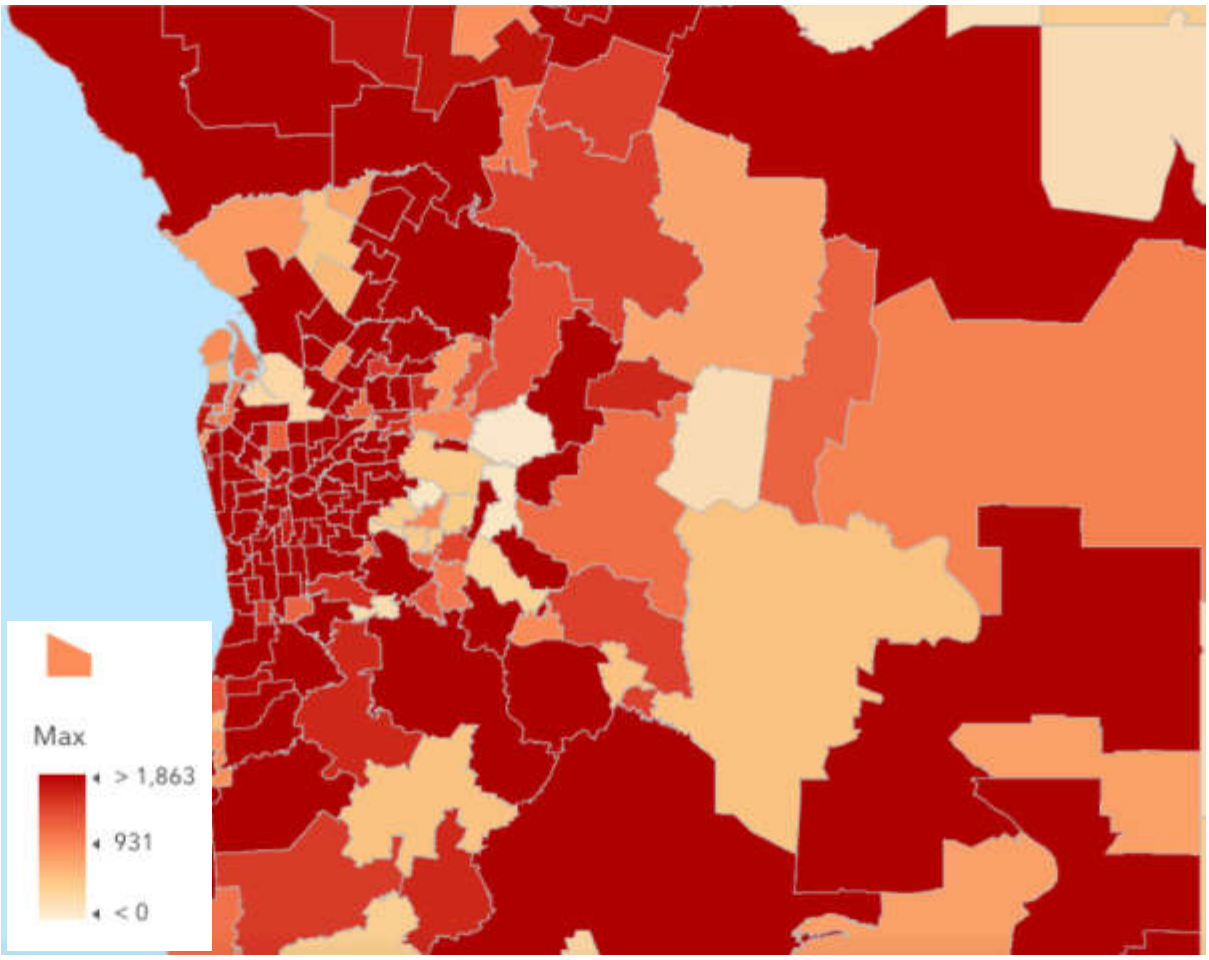




The combined impact of EV uptake on SAPN network

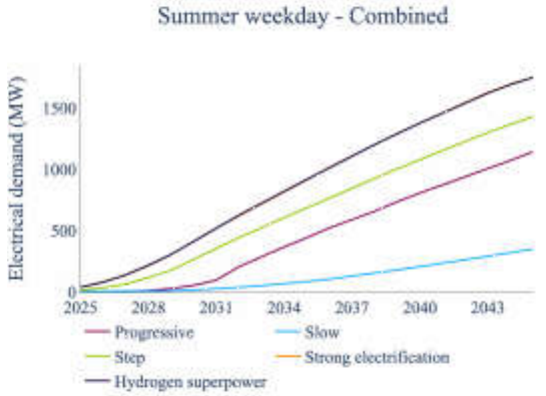
This section presents the key highlights of the aggregated charging of EVs. The heatmap presents the postcodes within the significant urban area (SUA) of Adelaide. The aggregated charging demand is high as the forecasted EV uptake in 2035 is 34% of the total vehicle sales. The maximum power demand of 30 MW in 2035 is forecasted at 5000 postcode on a winter weekend.

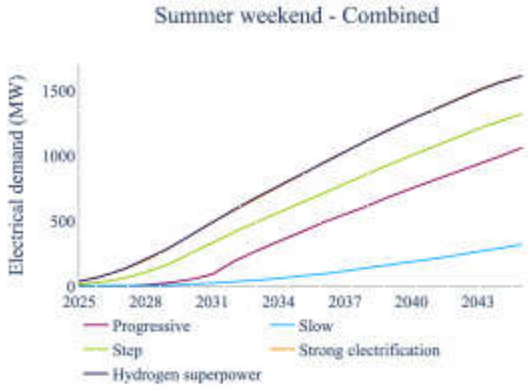
Spatiotemporal peak power demand for step change EV uptake scenario in 2035

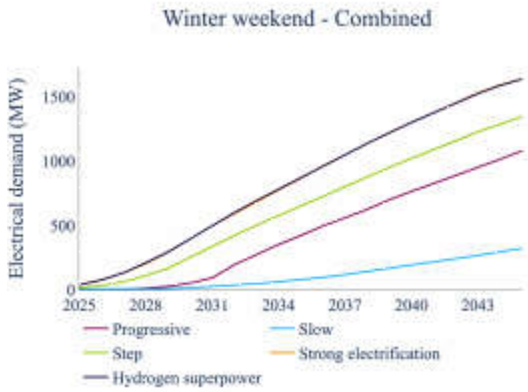


The following graphs presents the forecast of annual peak power demand due to charging of all the EVs.

Annual growth in peak power demand

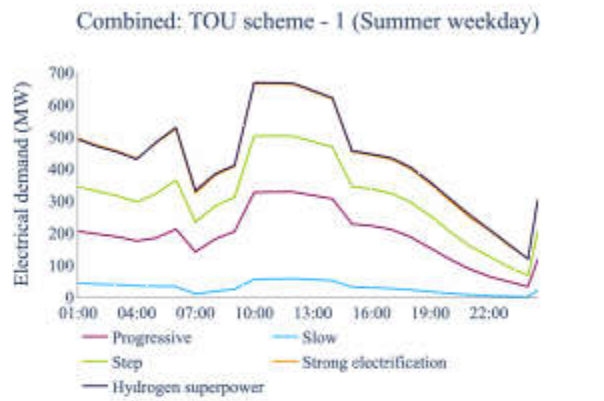


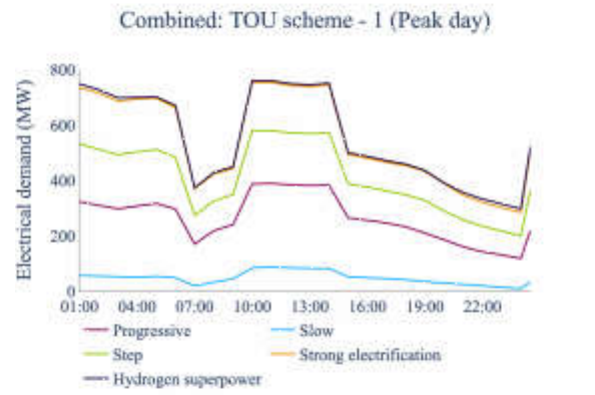


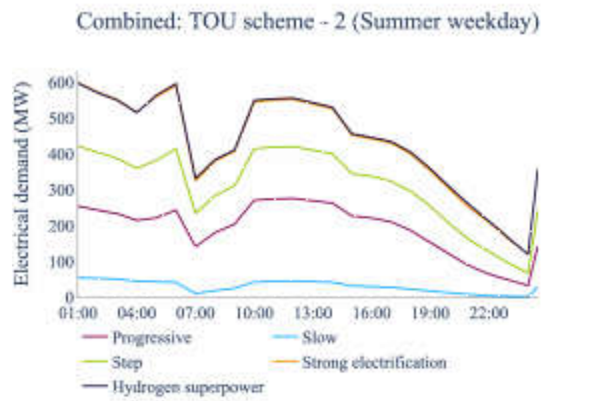


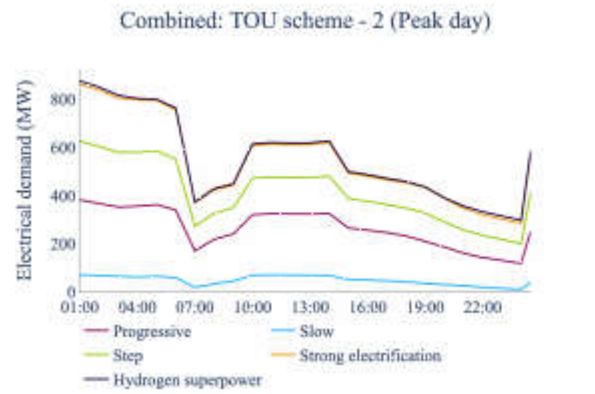
The following charts present a comparison between a normal day and a peak demand day. As defined previously, it is expected that the energy demand will rise on a peak demand day due to additional heating or cooling needs. A comparison is presented for all three TOU schemes.

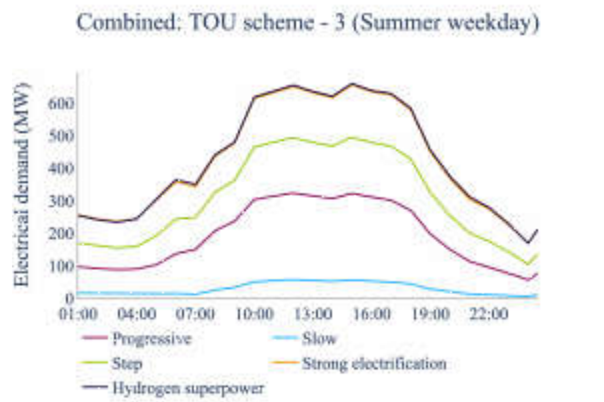
Comparison of peak demand day and summer weekday for all TOU schemes in 2035

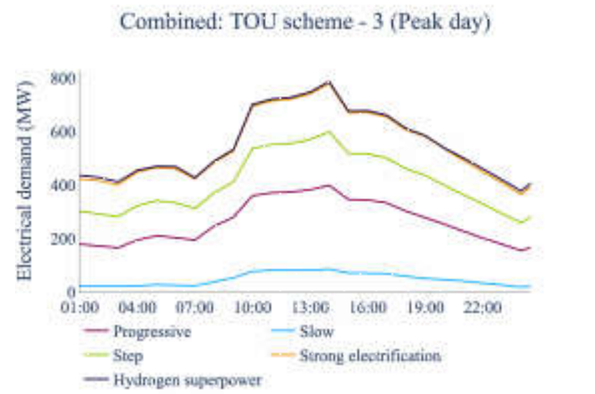












Appendix A - EV uptake scenarios

Electric Vehicle (EV) Uptake

Five assumption scenarios are modelled for both the peak power and energy models, based on AEMO's 2021 forecast:

1. Slow Change Scenario
2. Progressive scenario
3. Step Change Scenario
4. Hydrogen Superpower Scenario
5. Strong Electrification Scenario

The electric vehicle uptake scenarios by vehicle category are shown in the graphs below. These were separated into vehicle categories using data provided by AEMO.

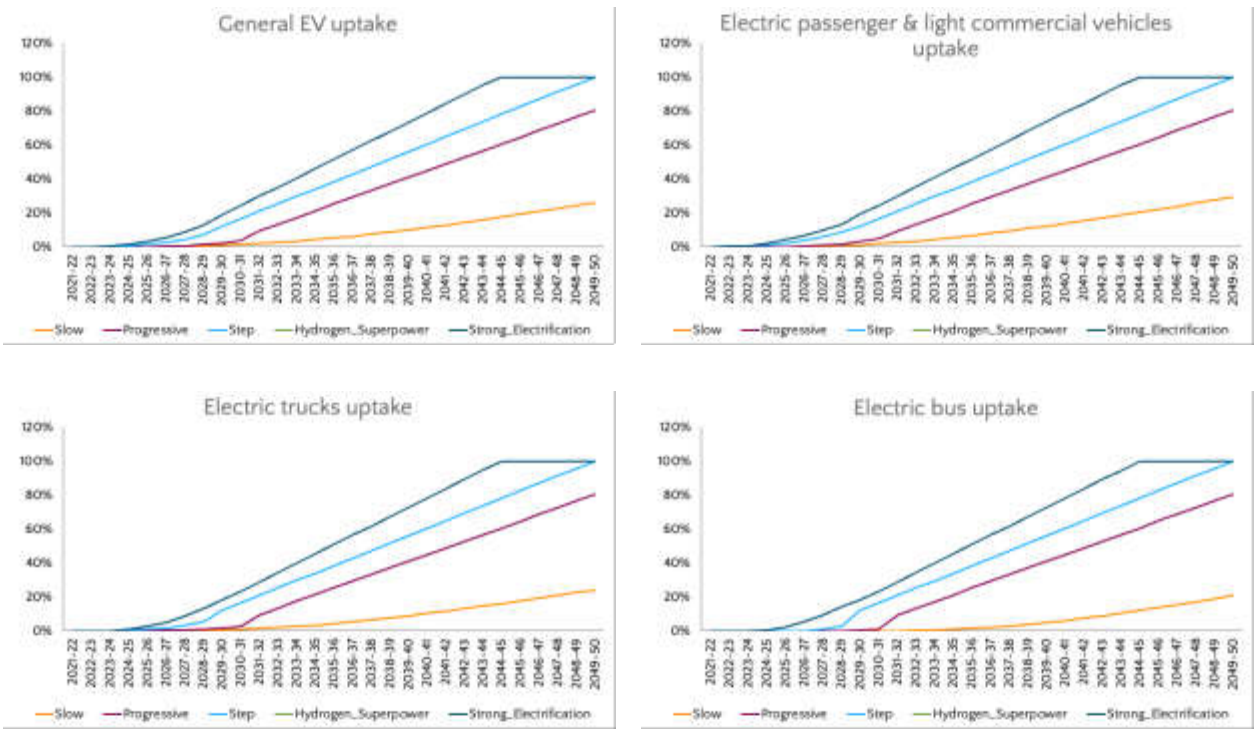
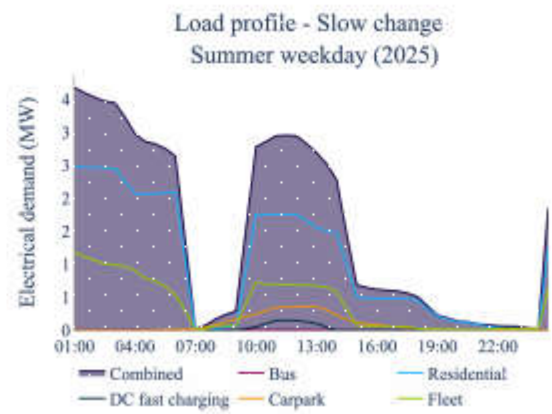


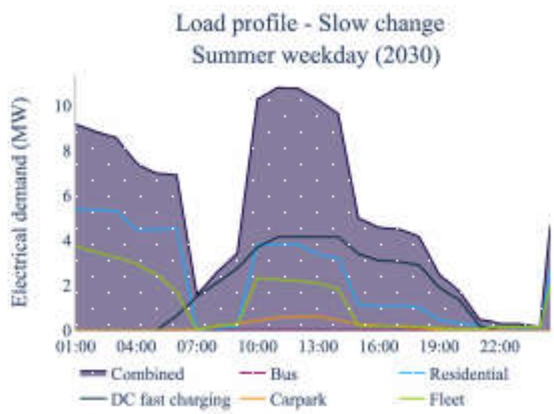
Figure 6: EV uptake by vehicle category

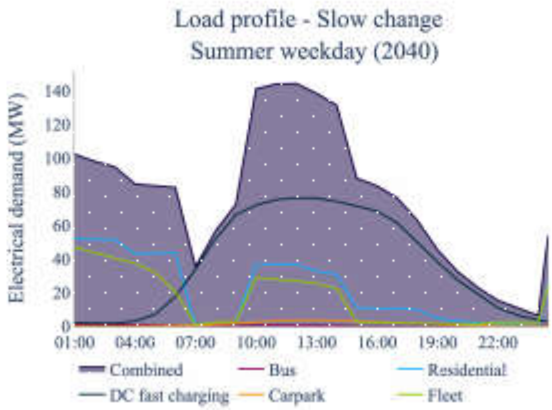
Appendix B - Power model summary outputs

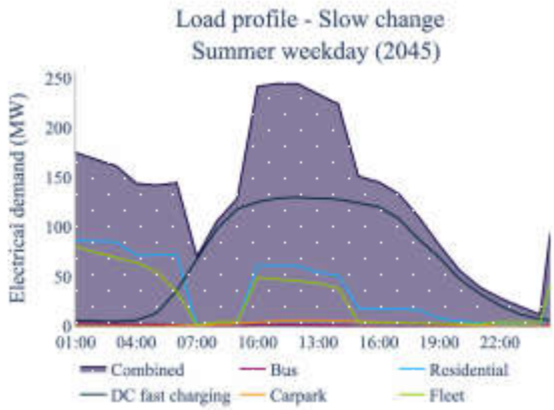
Slow Change Scenario

Summer Weekday

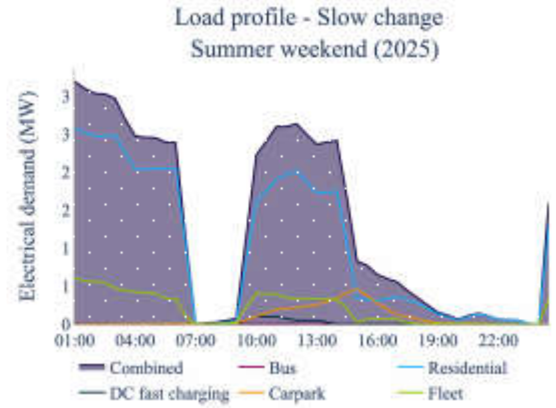


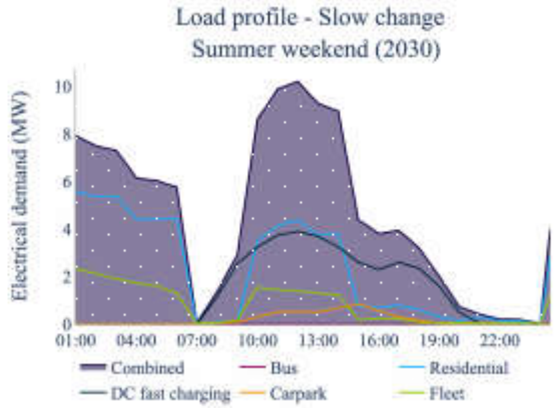


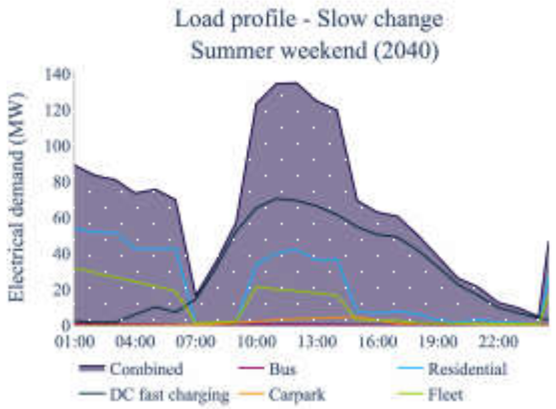


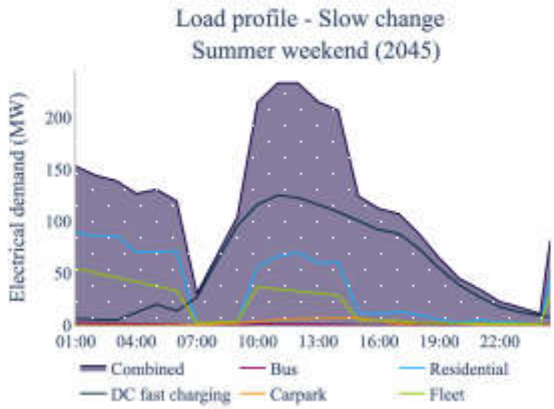


Summer Weekend

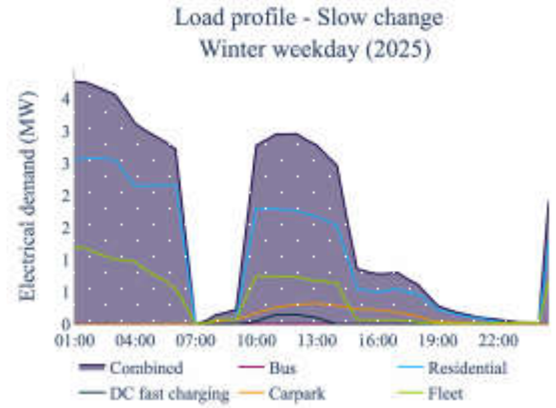


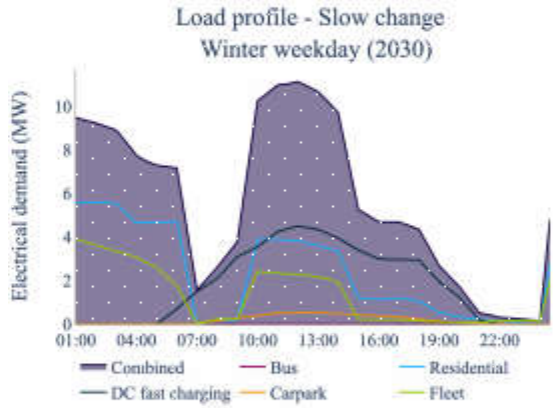


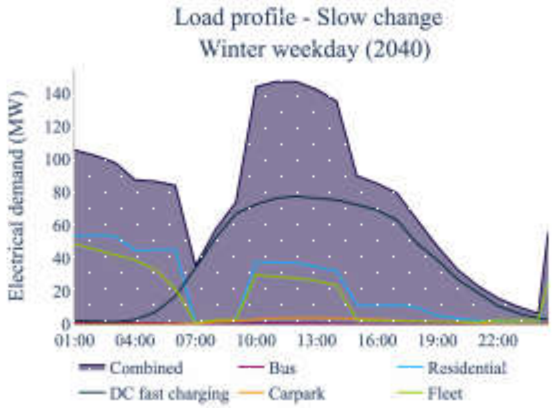


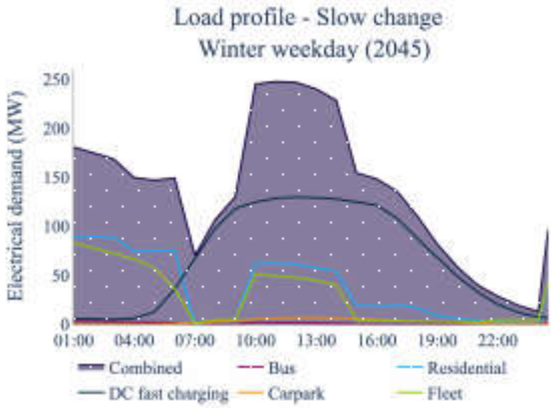


Winter Weekday

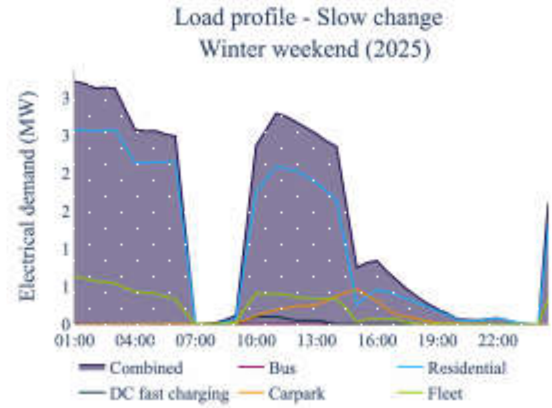


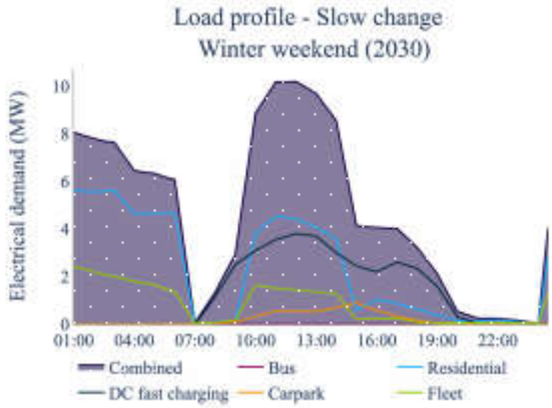


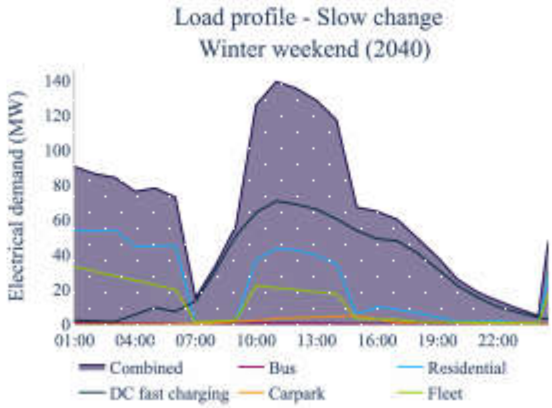


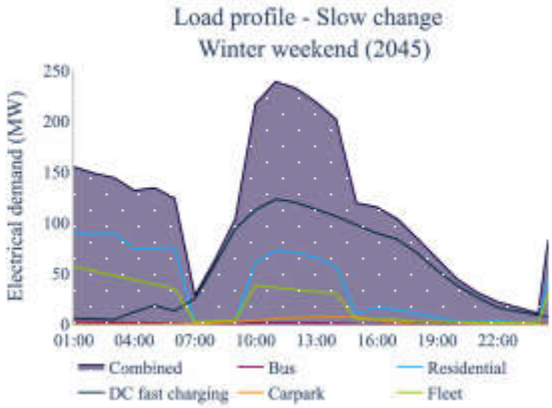


Winter Weekend



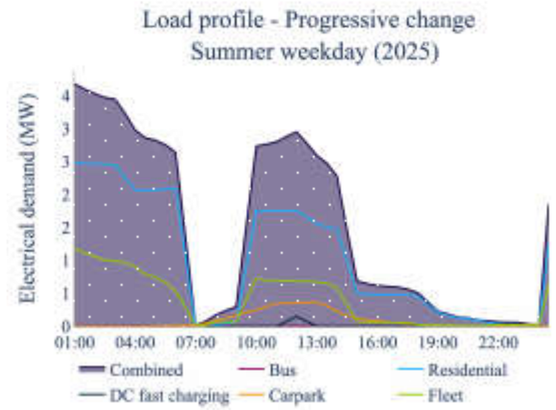


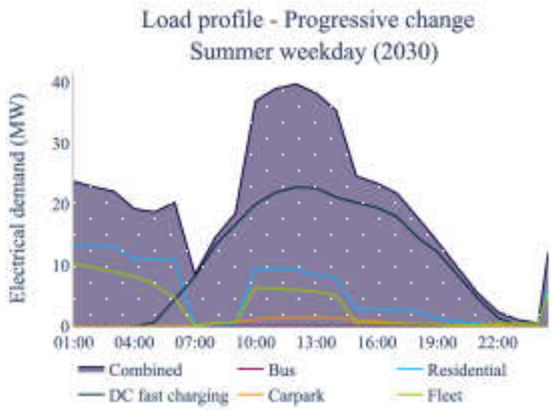


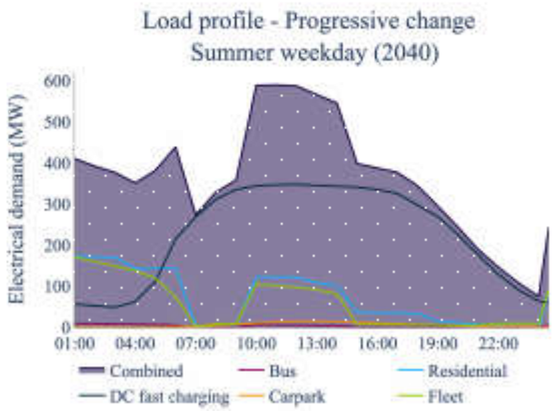


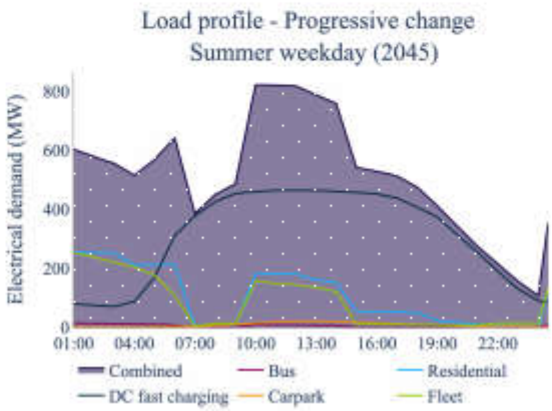
Progressive Scenario

Summer Weekday

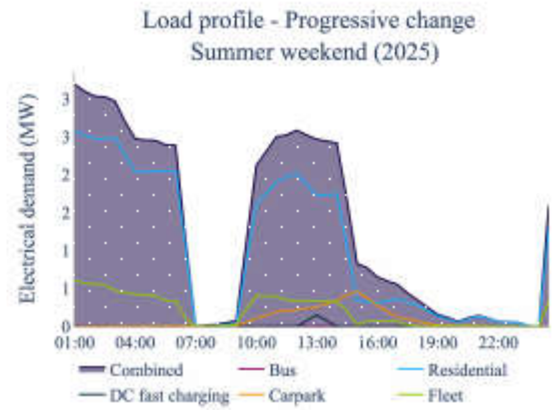


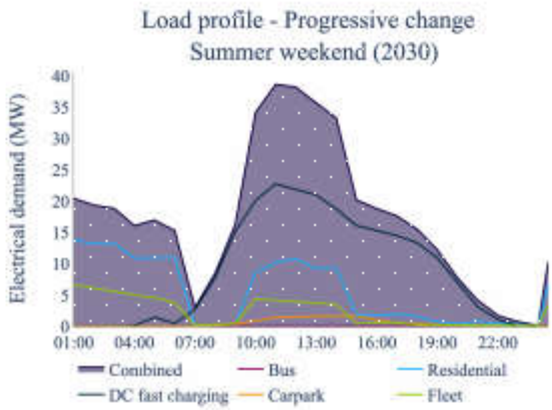


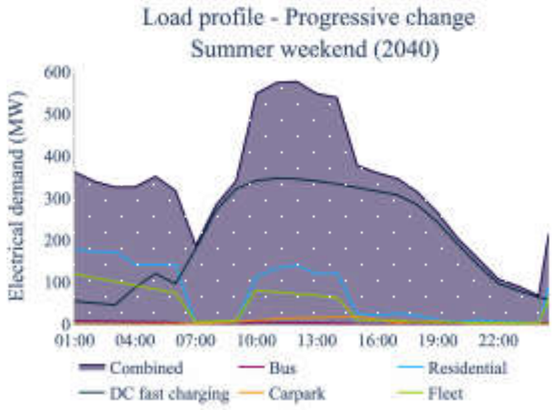


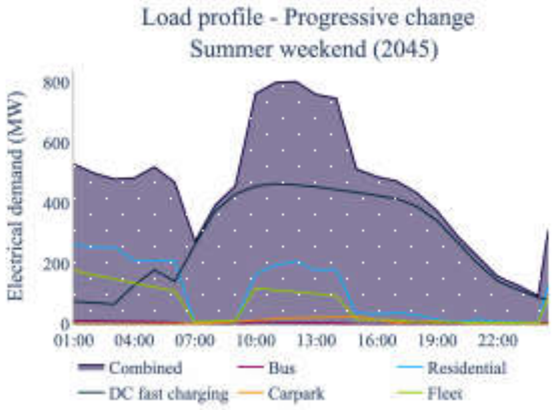


Summer Weekend

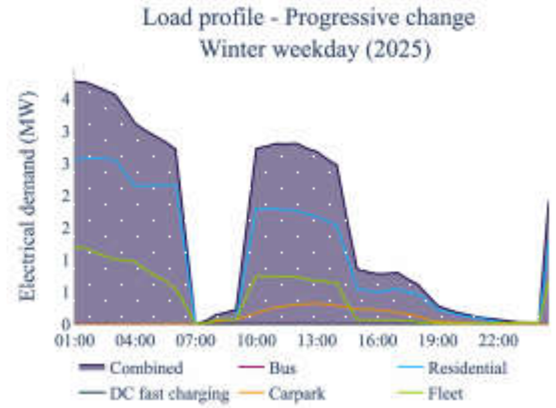


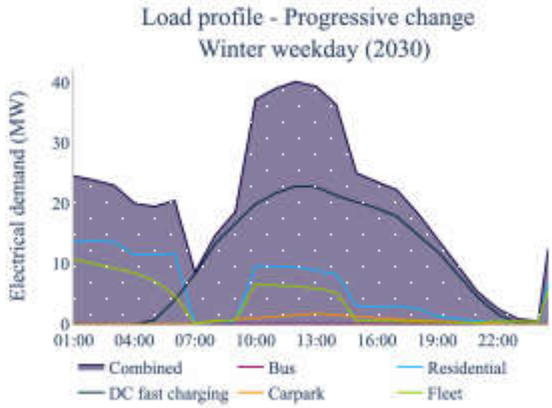


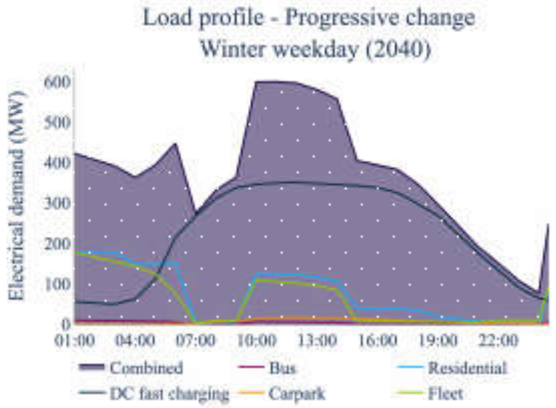


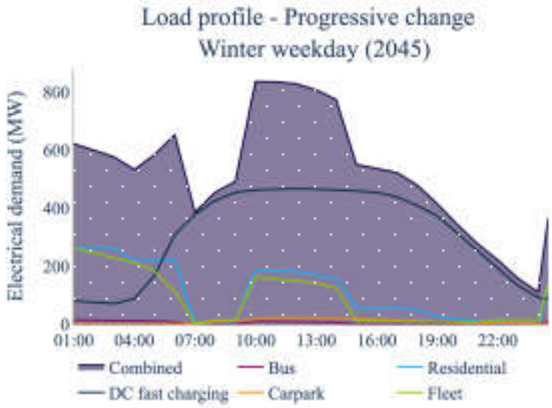


Winter Weekday

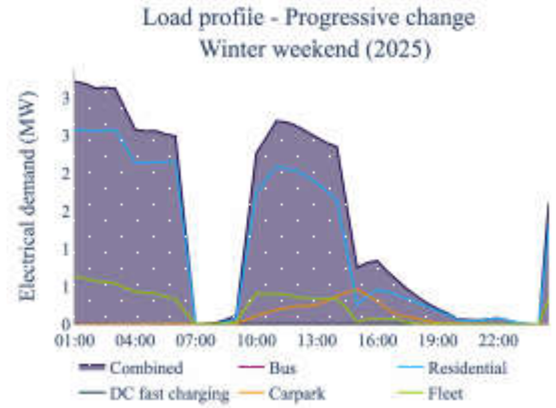


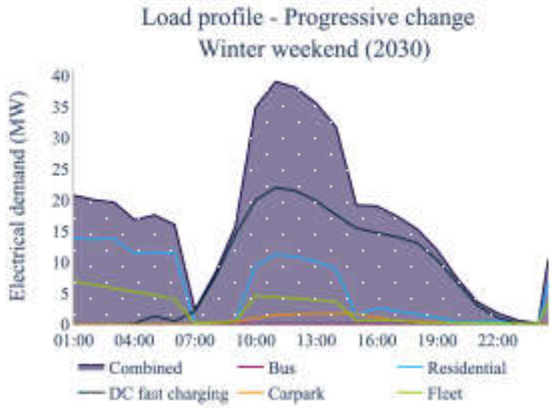


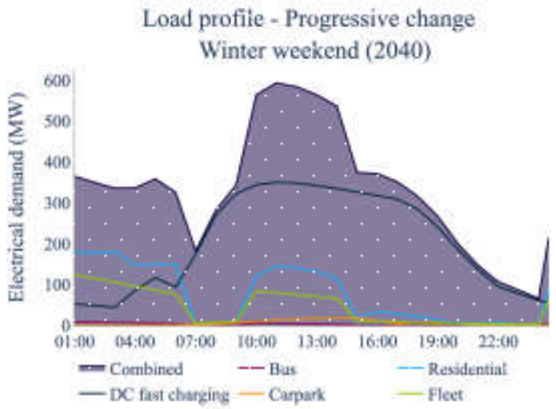


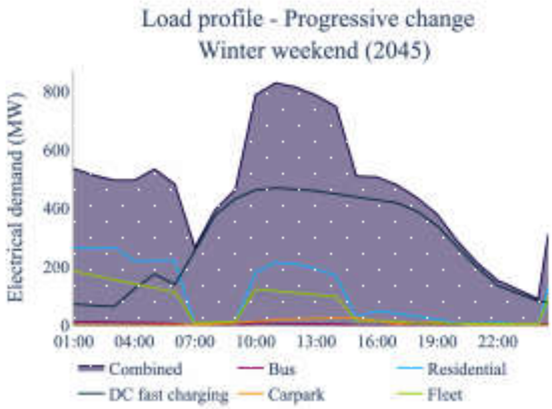


Winter Weekend


Load profiie - Progressive change
Winter weekend (2025)
Electrical demand (MW)
01:00 04:00 07:00 10:00 13:00 16:00 19:00 22:00
Combined
Bus
Residential
DC fast charging
Carpark
Fleet

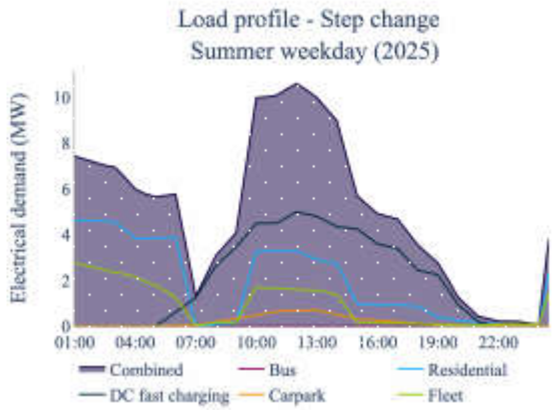

Load profile - Progressive change
Winter weekend (2030)
Electrical demand (MW)
01:00 04:00 07:00 10:00 13:00 16:00 19:00 22:00
Combined
Bus
Residential
DC fast charging
Carpark
Fleet

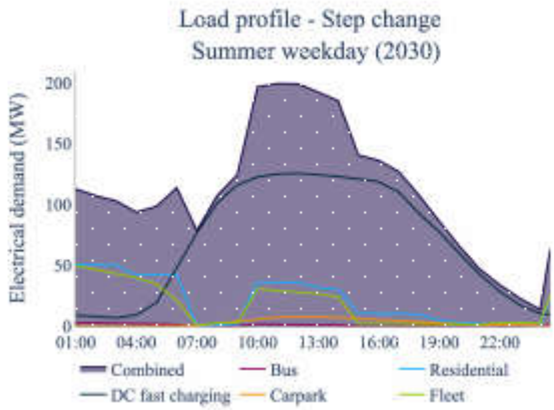

Load profile - Progressive change
Winter weekend (2040)
Electrical demand (MW)
01:00 04:00 07:00 10:00 13:00 16:00 19:00 22:00
Combined
Bus
Residential
DC fast charging
Carpark
Fleet

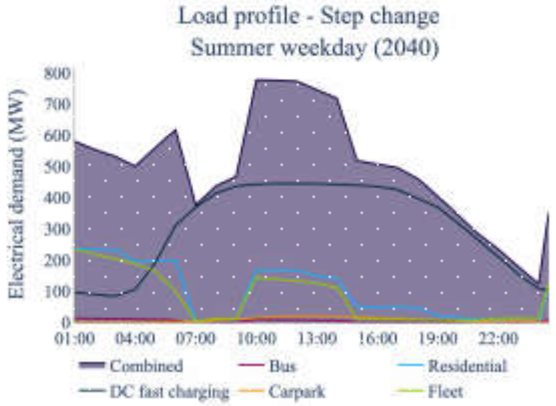

Load profile - Progressive change
Winter weekend (2045)
Electrical demand (MW)
01:00 04:00 07:00 10:00 13:00 16:00 19:00 22:00
Combined
Bus
Residential
DC fast charging
Carpark
Fleet

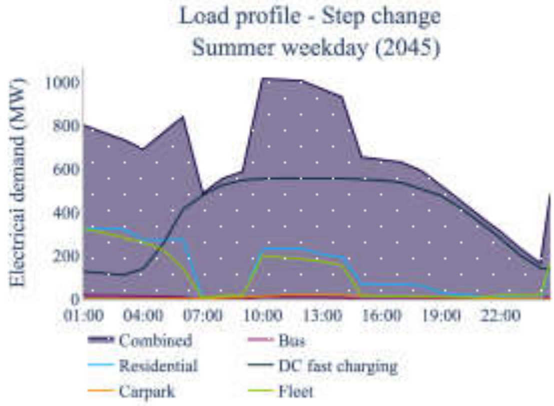
Step Change Scenario

Summer Weekday

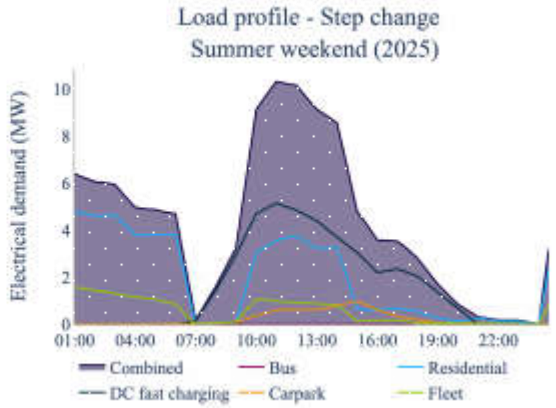


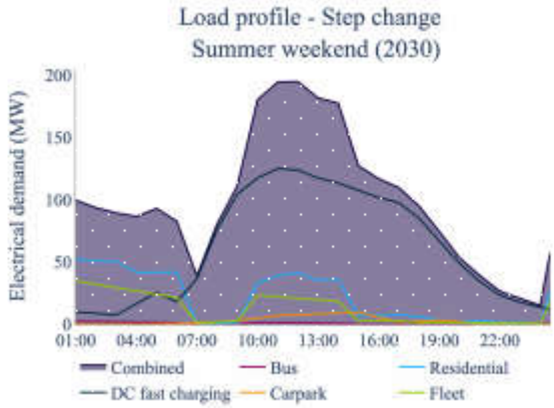


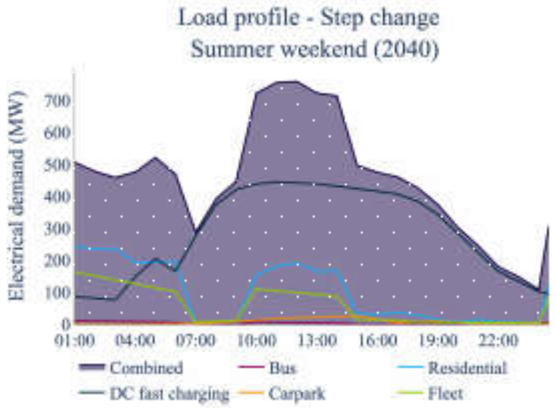


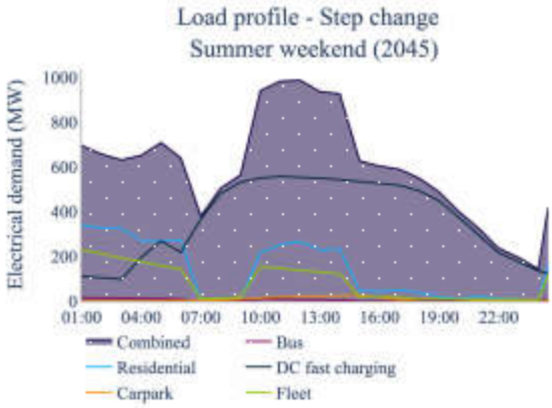


Summer Weekend

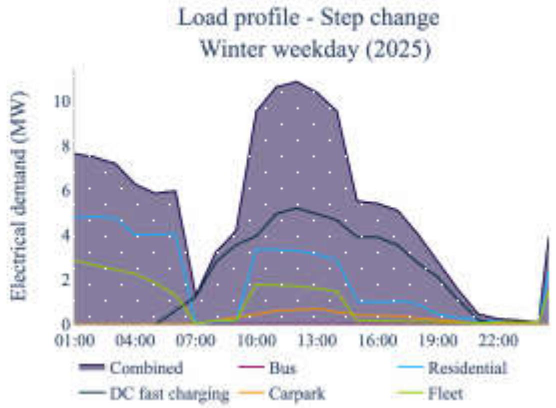


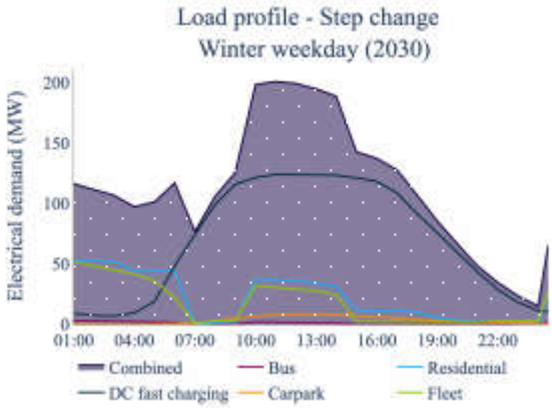


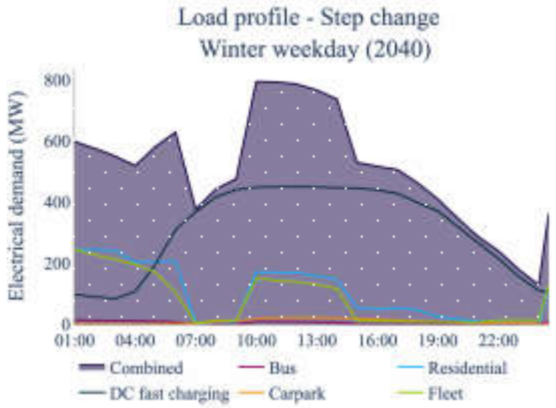


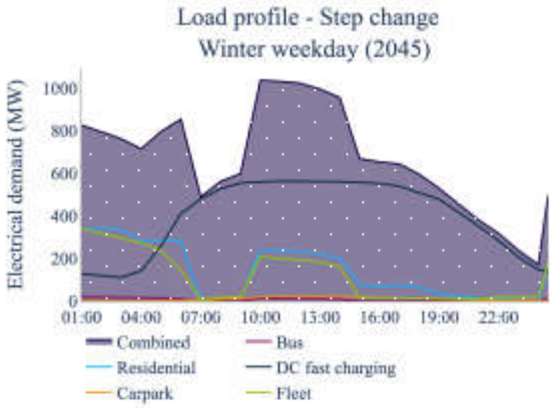


Winter Weekday

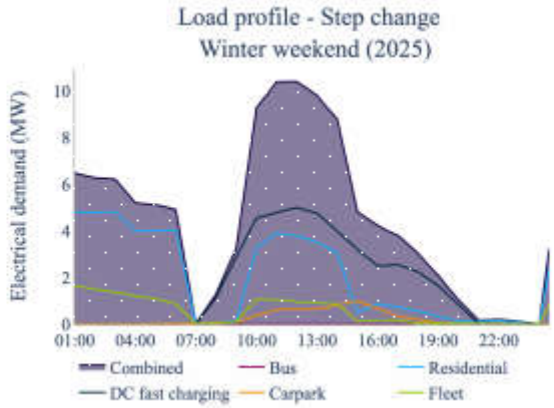


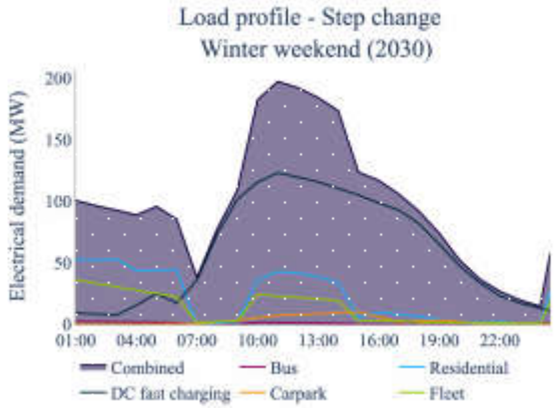


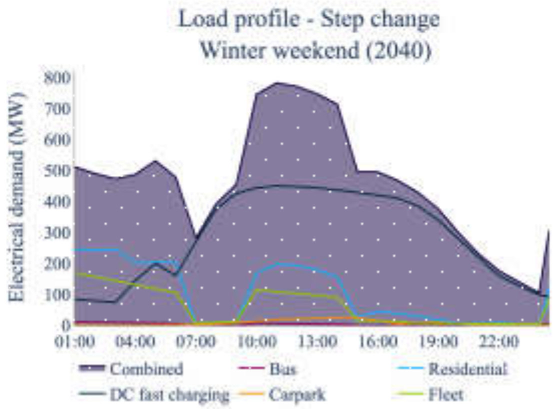


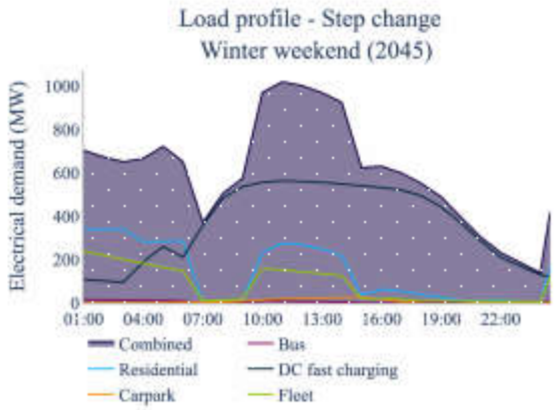


Winter Weekend


Load profile - Step change
Winter weekend (2025)
Electrical demand (MW)
0
2
4
6
8
10
01:00
04:00
07:00
10:00
13:00
16:00
19:00
22:00
Combined
Bus
Residential
DC fast charging
Carpark
Fleet

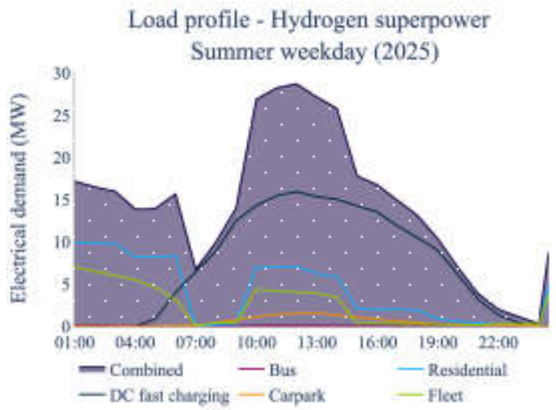

Load profile - Step change
Winter weekend (2030)
Electrical demand (MW)
0
50
100
150
200
01:00
04:00
07:00
10:00
13:00
16:00
19:00
22:00
Combined
Bus
Residential
DC fast charging
Carpark
Fleet

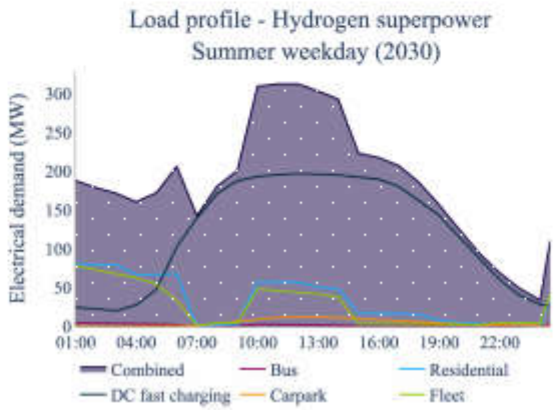

Load profile - Step change
Winter weekend (2040)
Electrical demand (MW)
0
100
200
300
400
500
600
700
800
01:00
04:00
07:00
10:00
13:00
16:00
19:00
22:00
Combined
Bus
Residential
DC fast charging
Carpark
Fleet

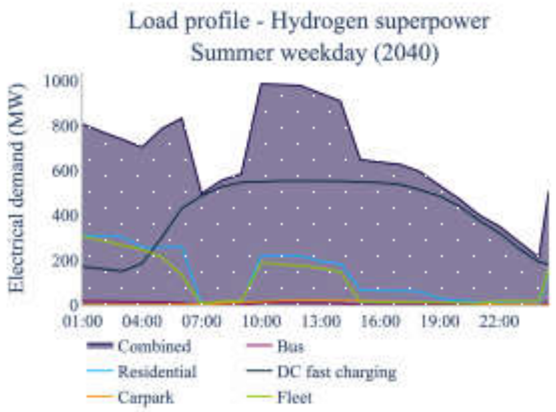

Load profile - Step change
Winter weekend (2045)
Electrical demand (MW)
0
200
400
600
800
1000
01:00
04:00
07:00
10:00
13:00
16:00
19:00
22:00
Combined
Bus
Residential
DC fast charging
Carpark
Fleet

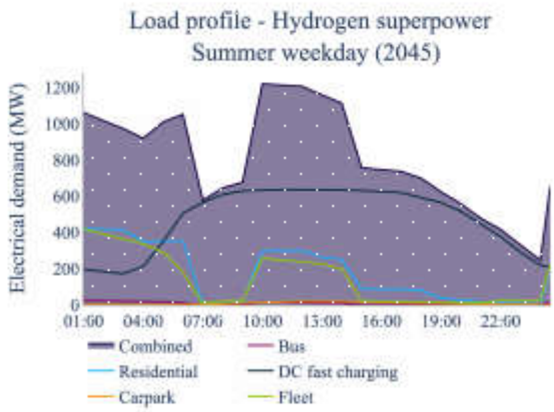
Hydrogen Superpower Scenario

Summer Weekday

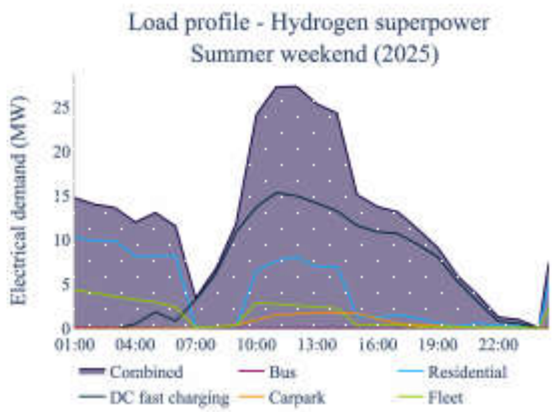


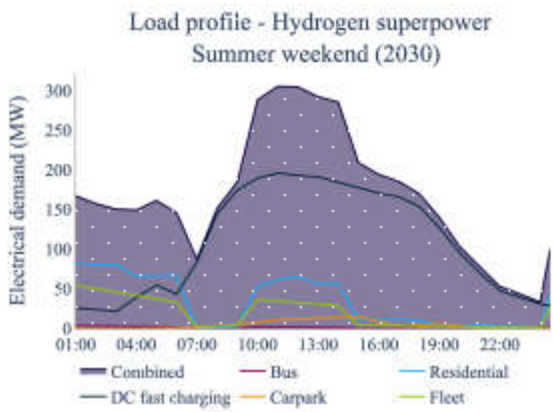


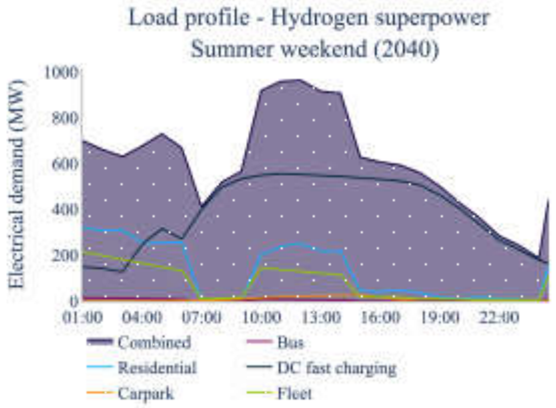


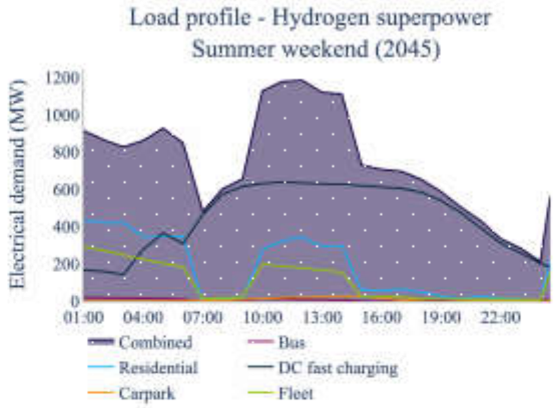


Summer Weekend

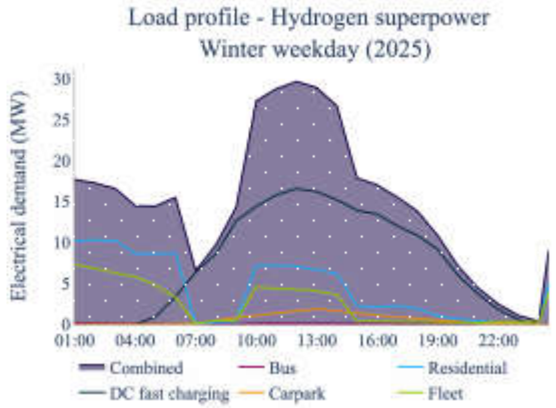


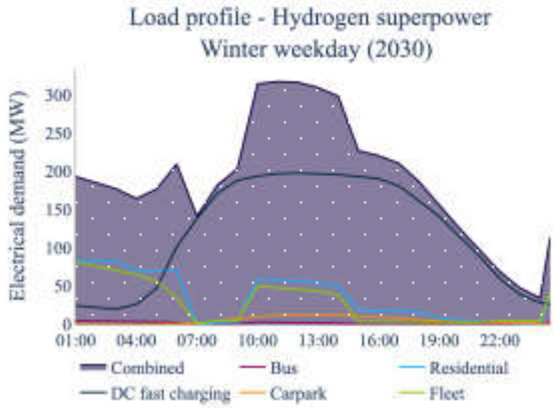


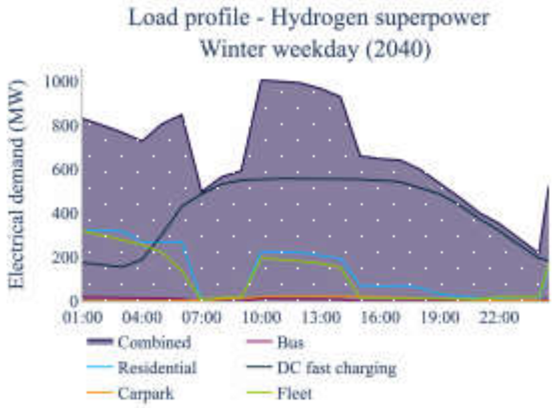


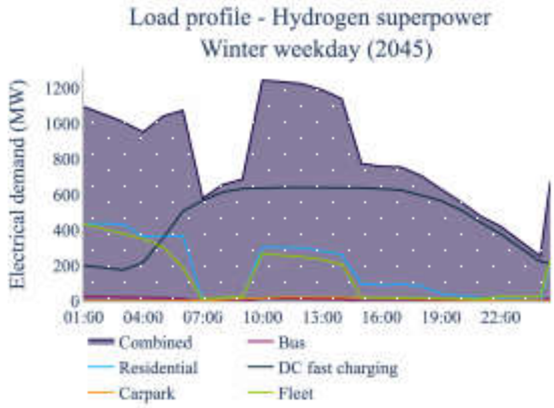


Winter Weekday

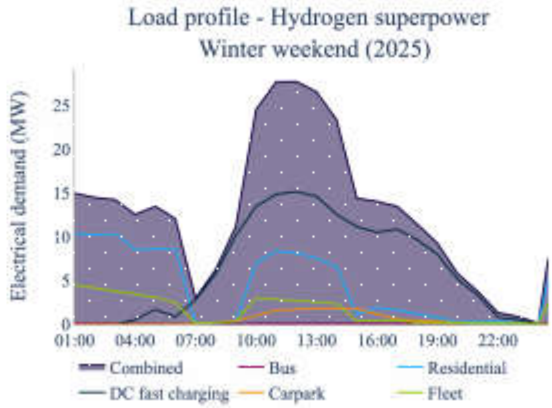


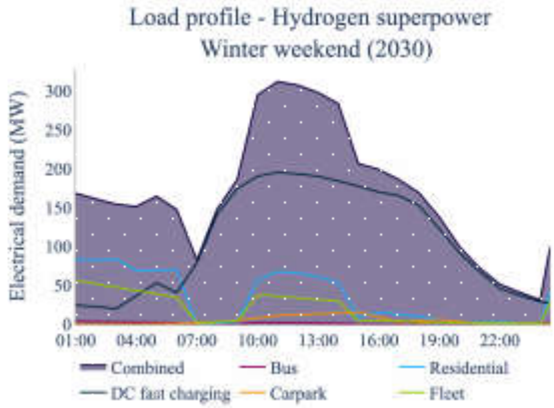


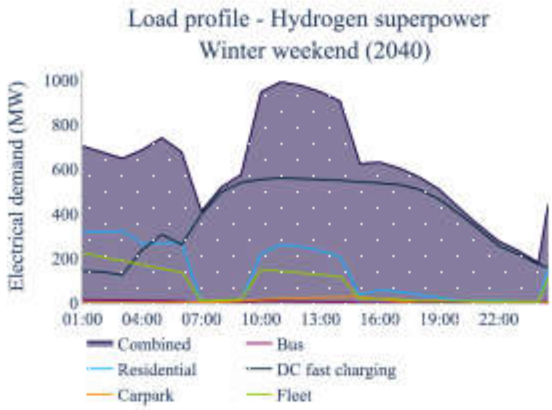


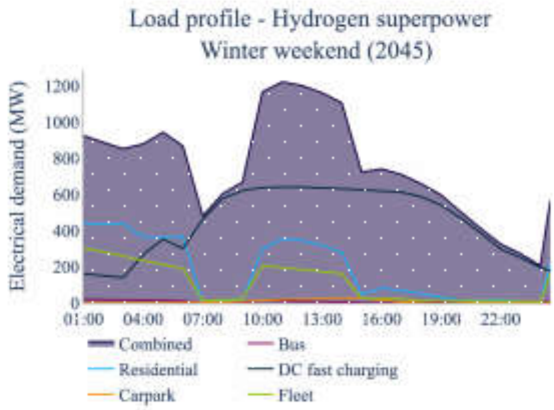


Winter Weekend


Load profile - Hydrogen superpower
Winter weekend (2025)
Electrical demand (MW)
0
5
10
15
20
25
01:00
04:00
07:00
10:00
13:00
16:00
19:00
22:00
Combined
Bus
Residential
DC fast charging
Carpark
Fleet

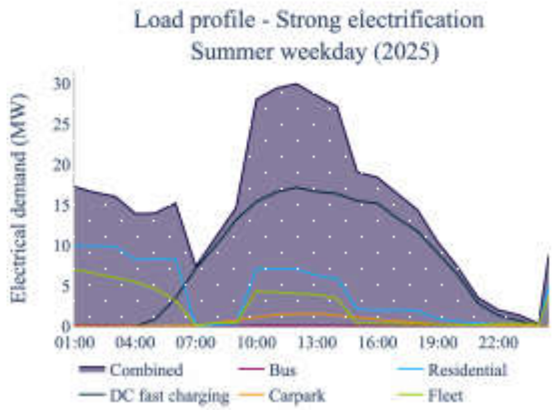

Load profile - Hydrogen superpower
Winter weekend (2030)
Electrical demand (MW)
0
50
100
150
200
250
300
01:00
04:00
07:00
10:00
13:00
16:00
19:00
22:00
Combined
Bus
Residential
DC fast charging
Carpark
Fleet

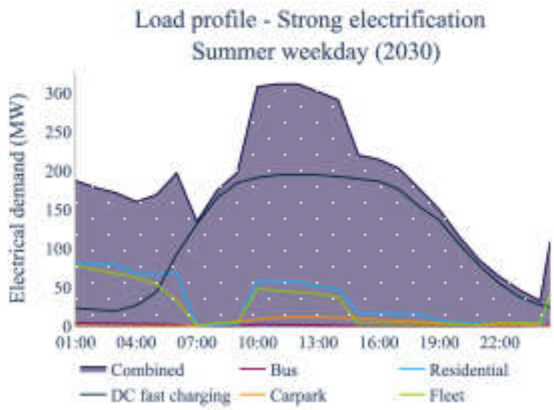

Load profile - Hydrogen superpower
Winter weekend (2040)
Electrical demand (MW)
0
200
400
600
800
1000
01:00
04:00
07:00
10:00
13:00
16:00
19:00
22:00
Combined
Bus
Residential
DC fast charging
Carpark
Fleet

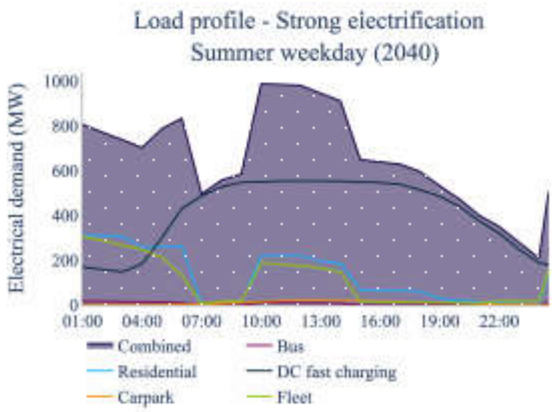

Load profile - Hydrogen superpower
Winter weekend (2045)
Electrical demand (MW)
0
200
400
600
800
1000
1200
01:00
04:00
07:00
10:00
13:00
16:00
19:00
22:00
Combined
Bus
Residential
DC fast charging
Carpark
Fleet

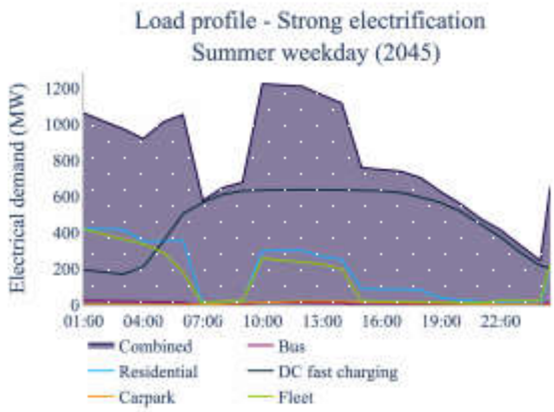
Strong Electrification Scenario

Summer Weekday

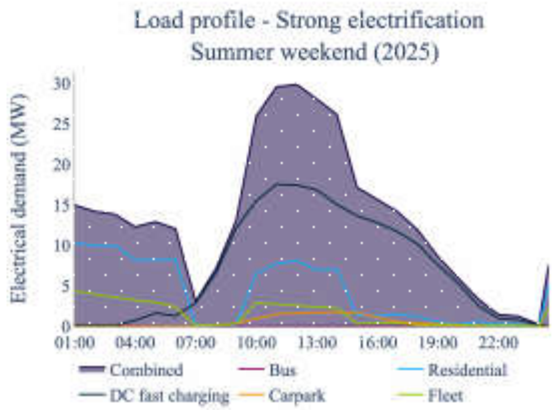


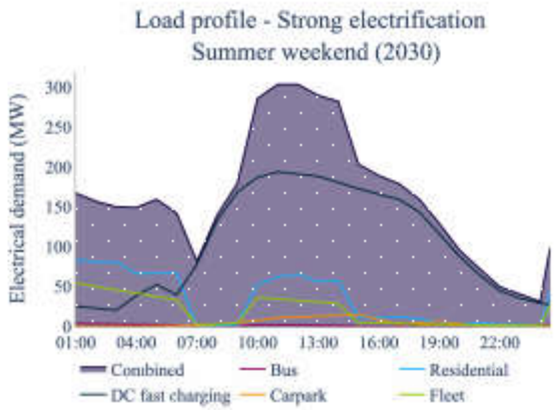


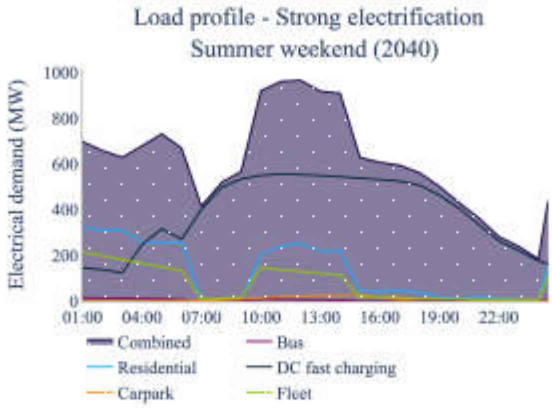


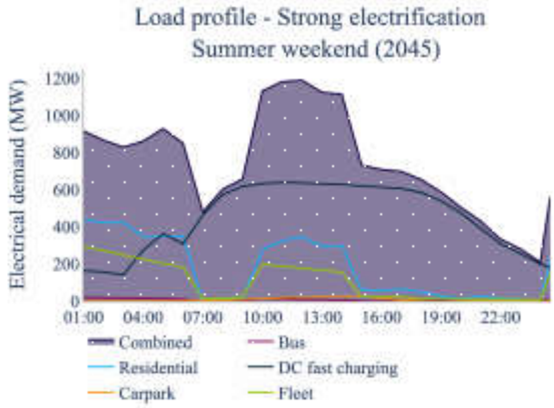


Summer Weekend

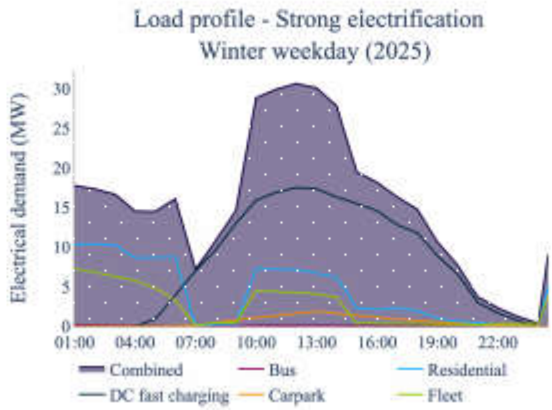


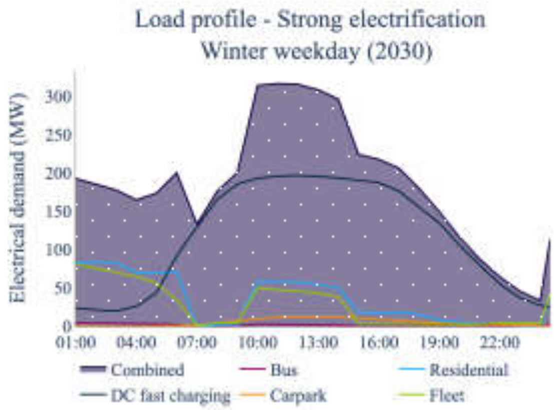


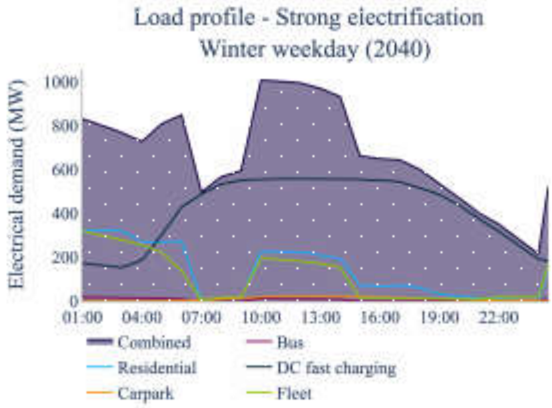


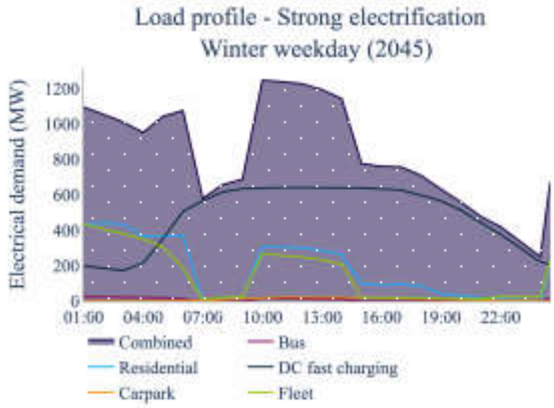


Winter Weekday

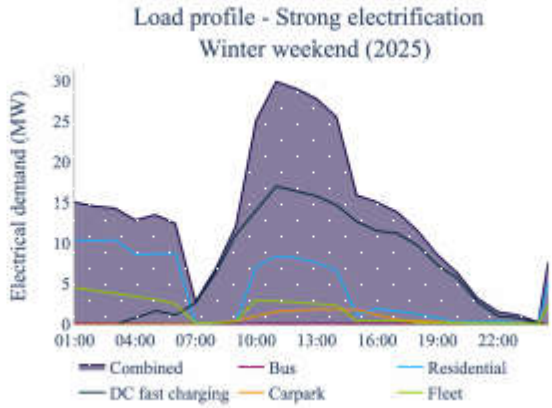


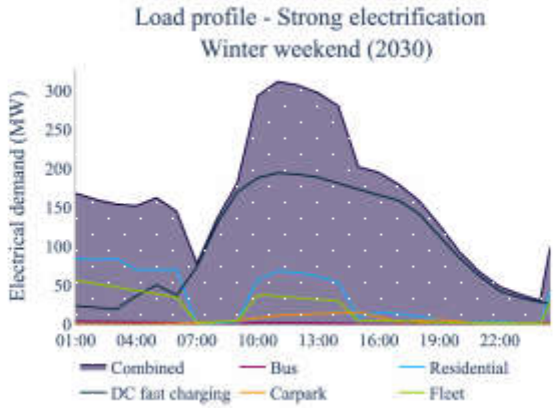


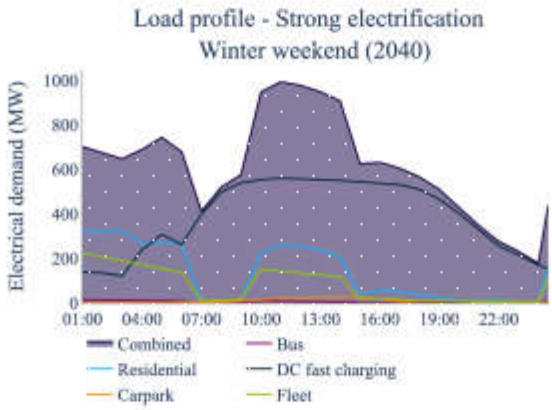


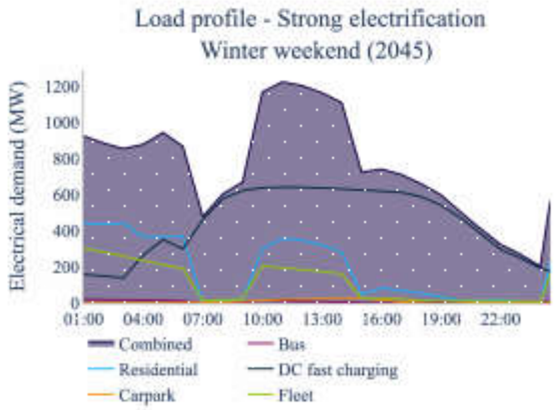


Winter Weekend


Load profile - Strong electrification
Winter weekend (2025)
Electrical demand (MW)
0
5
10
15
20
25
30
01:00
04:00
07:00
10:00
13:00
16:00
19:00
22:00
Combined
Bus
Residential
DC fast charging
Carpark
Fleet


Load profile - Strong electrification
Winter weekend (2030)
Electrical demand (MW)
0
50
100
150
200
250
300
01:00
04:00
07:00
10:00
13:00
16:00
19:00
22:00
Combined
Bus
Residential
DC fast charging
Carpark
Fleet


Load profile - Strong electrification
Winter weekend (2040)
Electrical demand (MW)
0
200
400
600
800
1000
01:00
04:00
07:00
10:00
13:00
16:00
19:00
22:00
Combined
Bus
Residential
DC fast charging
Carpark
Fleet


Load profile - Strong electrification
Winter weekend (2045)
Electrical demand (MW)
0
200
400
600
800
1000
1200
01:00
04:00
07:00
10:00
13:00
16:00
19:00
22:00
Combined
Bus
Residential
DC fast charging
Carpark
Fleet